Economic Shocks and Child Labour

Empirical Evidence from Uganda

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Declaration

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Abstract

This paper analyses the effect of economic shocks on children‘s work. From a theoretical point of view, economic shocks to poor households induce income shocks which may make child labour necessary to smooth consumption. But if the shock limits children‘s opportunities to work and reduces their marginal product of labour in certain activities, child labour is expected to decrease. The empirical part of this study is based on three waves of the Uganda National Panel Survey which cover the time period from 2009/10 to 2011/12. By applying Fixed Effects regression techniques, the empirical analysis indicates that a drought experienced by households is associated with significantly less child labour on the farm. Children‘s work participation in non-market labour activities, namely fetching water, significantly increases as a response to a drought. Market work and school attendance are not significantly affected. The findings suggest that children reallocate their labour supply as a response to shocks according to their marginal product of labour.

Contents

List of Figures

List of Tables

List of Acronyms

EA	Enumeration Area
FE	Fixed Effects
GNI	Gross National Income
i.i.d.	independently and identically distributed
ILO	International Labour Organization
LIC	low-income countries
LRA	Lord's Resistance Army
LSMS	Living Standards Measurement Study
OLS	Ordinary Least Squares
UBOS	Uganda Bureau of Statistics
UCW	Understanding Children's Work
UN	United Nations
UNHS	Uganda National Household Survey
UNPS	Uganda National Panel Survey

1 Introduction

Households in low-income countries (LIC) are exposed to several risks. Variation in rainfall can destroy the harvest or the illness of a family member can induce high out-of-pocket expenditures. When hit by such a shock, households rely on savings, sell assets or receive help within their social networks in order to smooth consumption.

Another coping strategy is child labour. By representing an alternative source of earnings, child labour can be used as a buffer against transitory income shocks. Economic theory and empirical findings suggest that some children in LIC are indeed used as an insurance in this way. However, children‘s work is not an efficient coping strategy if the marginal product of labour in certain activities is reduced by the shock. An economic shock may therefore lead to decreasing child labour depending on the opportunities for children to work and the type of shock that households experience.

So if economic shocks cause both fluctuations in household income and limited opportunities for child labour, how can the total effect of these shocks on child labour be described? To approach this question, this paper examines *the impact of droughts on children‘s work* by using panel data from Uganda, where child labour is widespread.

This paper adopts a microeconomic perspective. The theoretical model of Dillon (2013) is applied to understand the microeconomic reasoning behind child labour and shocks. Working children in Uganda are mainly engaged in agriculture. Since droughts are likely to reduce the marginal product of labour on the family farm, the hypothesis is that child labour will decrease if households experience a drought.

The empirical analysis is based on representative household survey data. Three waves of the Uganda National Panel Survey (UNPS) are used to analyse the effect of shocks on different forms of child labour. Survey rounds cover the time period from 2009/10 to 2011/12 and are part of the World Bank‘s Living Standards Measurement Study (LSMS) project. To the best of the author‘s knowledge the dataset has not been used in any peer-reviewed economic paper so far[1].

Disentangling the impact of transitory economic shocks on child labour is difficult because of the complex relationship between a family‘s living standards and child labour decisions. The empirical approach in this paper particularly accounts for these

[1]Parts of the survey were used in a study on young children‘s food consumption in low- and middle-income countries (Huffmann et al. 2014).

issues by applying Fixed Effects (FE) regression techniques. The empirical identification strategy largely follows Beegle, Dehejia and Gatti (2006).

This paper contributes to the literature on child labour in several ways. First, it provides empirical evidence for shock-specific adjustments of children‘s work according to a child‘s marginal product of labour in different activities. Results indicate that the experience of a drought within a household is associated with significantly less farm work of children. Children‘s participation in fetching water significantly rises, other things being equal. Second, rich survey data makes it possible to study children‘s work in market as well as in non-market labour activities. Focusing on economically active children only has been criticised by various experts. This study does not find statistically significant linear dependence of children‘s market work on drought. This is why the analysis shows that non-market labour activities, namely fetching water and working in agriculture, are crucial to fully understand children‘s working patterns when families are exposed to shocks.

This study considers child labour as a socially undesirable response to economic shocks. According to Satz (2003), moral concerns and normative judgements cannot be removed when studying child labour. Features such as children‘s weak agency, underlying inequalities between societies or families and its potential to harm make it difficult to eliminate any moral dimension. To cope with these difficulties, the following chapters do not discuss any consequences of child labour related to health or educational outcomes. Policy implications are also not derived.

The remainder of the paper is organised as follows. Chapter 2 focuses on the existing literature on child labour. Definitions of child labour are explained in chapter 2.1. Chapter 2.2 discusses theoretical and empirical work which analyses the effect of economic shocks on child labour. The microeconomic model of Dillon (2013) is presented as the conceptual framework of this enquiry in chapter 3. Chapter 4 concentrates on the empirical analysis. A closer look at descriptive data and at the broader context of the Ugandan economy is taken in chapter 4.1. The structure of the data set and the variables used in the analysis is described in subsection 4.2. Chapter 4.3 explains the empirical approach. Its results are illustrated in chapter 4.4 and robustness checks follow in subsection 4.5. Limitations of the empirical analysis are discussed in chapter 4.6. The last chapter summarizes the results and draws conclusions.

2 Literature review

2.1 Definitions of child labour

When talking about child labour, many experts and policy-makers refer to the guidelines of the International Labour Organization (ILO). The ILO‘s definition of child labour is based on the ILO Conventions 138 and 182 as well as on the United Nations (UN) Convention on the Rights of the Child (ILO 2007). A child is defined as any person below the age of 18 years. The ILO claims a minimum age for entry to work of 15. The minimum age may be set to 14 in some LIC but it should not be lower than the age at which the compulsory schooling in this country ends. Children who work in the so-called worst forms of child labour are always classified as child labourers. The worst forms of child labour include - among others - slavery, prostitution and hazardous work that is likely to harm children‘s health or development. Whether children who participate in other, non-hazardous types of work are officially considered child labourers or not depends on the interaction between the child‘s age and the type of work she or he is doing. Children at the age of 12 or 13 may already be allowed to do light work. In this case they are not classified as child labourers. Categories such as hazardous work or light work require further specification by national legislation.

Most empirical studies and statistics refer to economically active children, i.e. children involved in economic activity. This definition includes wage workers, employers, own-account workers and members of producer cooperatives but also unpaid family workers, apprentices, members of the armed forces as well as the unemployed (Edmonds 2008). Market work covers the same categories but excludes the unemployed. Market work can be done both outside and inside the child‘s household (Edmonds and Pavcnik 2005). Domestic work, on the other hand, refers to non-economic work[2], but this term is not always used precisely. If children provide services for their families such as taking care of siblings or the elderly, collecting firewood, cooking or making small repairs, these activities are subsumed as domestic chores or household chores. Following Edmonds and Pavcnik (2005), this paper sees all aspects of child work included in the term "child labour". In the empirical part of the paper the definition will be further specified, based on the Ugandan context and the data.

[2]Edmonds (2008) defines non-economic work as the participation in productive activities that are not covered by the United Nations System of National Accounts.

Even though several empirical studies do not include domestic chores[3], recent literature widely agrees that, in order to get a comprehensive understanding of children's work, these activities should be taken into account as well. This argument is particularly supported by the empirical fact that most children in LIC perform domestic duties: In 2000 almost two-thirds of children aged 5 to 14 in 36 LIC assisted their families with domestic chores. 25 % participated in market work in general and only 2 % worked for wages (Edmonds and Pavcnik 2005).

The detailed definitions of child labour used in the literature do often not correspond to the public perception of child labour in developed countries. Only very few studies, for instance, explicitly investigate worst forms of child labour [4]. Instead, most empirical work focuses on unpaid young family workers that support the household‘s business or agriculture. This is why Edmonds regards many studies on child labour as "child time allocation studies" (Edmonds 2008: 3611). He argues that most economic research avoids moral arguments by quantifying the costs of child labour in terms of human capital accumulation instead. Additionally, people's perceptions of a child, a child's duties and child labour are greatly related to social norms that vary across countries. In the context of some African traditions childhood rather refers to a specific position in social hierarchy than to any biological age. Twum-Danso (2005) points out that in this setting children already have certain responsibilities for their families and communities.

[3]See, for example Cogneau and Jedwab (2012), Dammert (2008), Dumas (2012), Duryea, Lam and Levison (2007), Heltberg and Lund (2009) or Wahba (2006).

[4]French (2010) examines the impact of child labour on health, education and welfare by looking at an export-oriented manufacturing center for leather shoes in Brazil where toxic glues are used. Edmonds and Shrestha (2014) analyse the effect of scholarships on schooling and child labour in the export-oriented industry of handmade carpets in the Kathmandu Valley in Nepal.

2.2 Economic shocks as determinants of child labour

For the last 15 years literature on child labour has been growing rapidly. Early work mainly identifies poverty and low income as the driving force behind child labour. This is, for instance, what Basu and Van (1998) conclude in one of the first seminal papers[5]. However, the link between income and child labour is complex. Poor and rich families are likely to differ not only in income but also in omitted factors which affect child labour decisions as well (Edmonds 2008). Child time allocation and the economic conditions of a household are basically joint outcomes of one decision-making process. So recent work mainly regards child labour as a symptom of poverty and not as its causal consequence (Edmonds and Pavcnik 2005, Goto 2011, Satz 2003).

Relating child labour to temporary economic shocks is what most of the lately published studies do instead. The main assumption is that children‘s work can be used as a buffer of households against temporary income shocks to smooth consumption. Children then work more to cope with the shock (argument I). On the other hand, shocks can affect the marginal product[6] of labour in certain activities which may reduce children‘s work (argument II). The following sections take a closer look at different arguments, channels and determinants that are discussed in the literature.

If households in LIC face shocks such as crop loss or the death of a family member, their current income is likely to be adversely affected. However, according to the permanent income hypothesis, such temporary income shocks only slightly change consumption patterns of the households. Families rather smooth consumption over lifetime (Edmonds and Shrestha 2014).

Households can make use of various strategies to smooth consumption. Informal coping mechanisms are particularly relevant in LIC where formal credit and insurance programs provided by the market are hardly available. Informal strategies can mean selling physical assets, drawing on savings or reciprocally exchanging gifts and loans in the community (Morduch 1999). The empirical literature shows that such informal

[5]The conceptual framework of Basu and Van (1998) is based on two fundamental assumptions: The luxury axiom states that children are sent to participate in the labour market only if the household cannot meet its subsistence needs without additional income generated by the child. The substitution axiom defines adult labour and child labour as substitutes. Although the model has highly influenced the literature, it has been criticised for its strict assumptions (Cigno and Rosati 2005: 6, Fors 2012).

[6]The literature does not always distinguish between the marginal product of labour and marginal productivity. Following Cameron and Worswick (2003) and Dillon (2013), this study uses the term "marginal product of labour".

insurance strategies and networks are in place even though they do not always work efficiently[7]. The efficiency of informal insurance networks also depends on the type of shock. If the shock is covariate (or aggregate) - which means that it affects a whole village, area or country -, the benefits of such coping mechanisms within a community are limited (Jensen 2000). Informal networks are seen as more efficient in case of idiosyncratic shocks, i.e. if the shock only affects one individual or one household (Heltberg and Lund 2009). Agricultural shocks like floods, droughts or pest as well as commodity price shocks are seen as aggregate shocks while unemployment or illness of a household member are considered idiosyncratic shocks (De Janvry et al. 2006).

One consumption smoothing strategy that may have significant welfare implications is to adjust household labour supply. Cameron and Worswick (2003) argue that welfare effects depend on a change in the number of total hours worked as a response to the shock. If households only reallocate labour supply by substituting family farm activities by wage employment it does not lower leisure and hence welfare. Investigating responses of Indonesian households they find that households do not increase their total hours of work as a response to crop losses but reallocate labour supply between different types of work. The results confirm Kochar‘s (1999) idea that labour supply adjustments are essential for consumption smoothing. Yet she finds that in rural India hours of work do increase as a response to agricultural shocks.

While Kochar (1999) focuses on adult labour supply, labour supply responses to shocks may also imply sending children to work (Beegle, Dehejia and Gatti 2006). This is why children can be seen as some kind of insurance (argument I). By testing this relationship directly, empirical research shows that temporary economic shocks which hit households in LIC can indeed give rise to child labour.

Jacoby and Skoufias‘ (1997) paper is one of the first and most influential studies which examines this relationship theoretically as well as empirically. The authors study child labour as a coping strategy along with responses to schooling. They assume that child labour leads to unstable school attendance which - as a consequence - reduces a child‘s future productivity. "To assess this cost of using child labour as insurance" (Jacoby and Skoufias 1997: 312) they develop a dynamic model of human capital investment under uncertainty. If consumption is insurable ex ante, i.e. if fi-

[7] See Bobonis (2009), Okamoto (2011), Robinson (2012), Rosenzweig and Wolpin (1993) or Townsend (1994) for detailed evidence.

nancial markets are complete, children‘s education is determined by rates of return only. Uninsured households, however, withdraw children from school when hit by an unanticipated income shock. Testing their model empirically based on data for rural India, they find that unanticipated income shocks significantly affect school attendance. Seasonal fluctuations in school attendance are seen as a form of self-insurance and as evidence for incomplete financial markets.

The assumption of children being used as insurance is also supported by Dillon (2013) who explicitly models child labour. Dillon analyses the impact of crop loss and morbidity at the intensive and extensive margin of children‘s market and domestic work based on cross-sectional household survey data for northern Mali. Applying a linear probability model, he finds hardly any significant effect of health shocks on children‘s work participation and school attendance. Small crop losses do not have any significant effect either. Only a large crop loss is associated with a significant increase in a child‘s probability to withdraw from school (by 12 percentage points) and to do farm work (by 24 percentage points). On the other hand, only health shocks significantly affect child labour at the intensive margin. Health shocks increase children‘s work in household enterprises by 2.6 hours and their time spent on child care by 1.8 hours. Dillon‘s findings suggest that whether child labour is used as a risk coping strategy highly depends on the type of shock and the type of work.

Alcaraz, Chiquiar and Salcedo (2012) study the impact of a negative shock on household remittance flows from the U.S. to Mexico caused by the 2008/09 global economic crisis. Domestic chores are not considered. The remittance shock causes a significant increase in child labour and a significant reduction in school attendance indicating that child labour is used as a strategy of households to cope with shocks. Children‘s probability to work rises by 10 percentage points. Probability to attend school declines by 16 percentage points. The change in children‘s work is mainly driven by households living in rural areas. Different pattern of child labour in rural and urban areas are discussed in various studies like Ersado (2005), Fafchamps and Wahba (2006) or Manacorda (2006). In contrast to children in urban areas, children in rural areas are mainly engaged in farm work. Besides, rural children tend to be more likely to attend school and work at the same time.

Beegle, Dehejia and Gatti (2006) test to what extent children are used as a buffer against transitory shocks in Tanzania. They measure income shocks by self-reported crop loss and include both market and domestic work. Using panel data, the authors find that income shocks significantly raise child labour. If their families are hit by an income shock, children‘s workload increases by 6.1 hours, other things being equal. Hours spent on domestic chores rise by an order of 50 %. Besides, children of households that experienced a shock are 20 percentage points less likely to be enrolled in school. The results also show that assets mitigate the impact of shocks. The authors conclude poorer households to be credit constraint, because they seem to use assets as buffer stocks. However, focusing on household assets is problematic here since they are likely to be correlated with a child‘s productivity in certain activities (Edmonds 2008)[8]. The idea is that some assets can lead to significantly higher child labour if these assets trigger labour demand that children are able to meet efficiently. For example, a child whose parents own land may work more compared to children of landless families if he or she can help at the household farm.

This argument has been widely discussed in the literature because it emphasizes the complex link between living standards and child labour. Regarding land ownership this is what Bhalotra and Heady (2003) call the wealth paradox: they provide evidence that in rural Pakistan and Ghana on average farm size increases child labour and lowers school attendance, even though land holdings are associated with higher wealth and, thus, with lower child labour. According to the authors, this finding is mainly caused by imperfect land and labour markets, which make child labour necessary to meet the labour demand on the household‘s farm. The decision is determined by the return to children‘s work relative to the return to education. Given the fact that the marginal product of labour increases in farm size, land holdings are relevant.

Hazarika and Sarangi (2008), Maldonado and González-Vega (2008) as well as Menon (2010) examine the marginal product of child labour with reference to access to credit. Access to credit is usually seen as a way to raise household income and to improve a family‘s ability to overcome transitory shocks (Maldonado and González-Vega

[8]Disentangling the effect of credit constraints is, in general, difficult because of considerable endogeneity issues between credit rationing and child time allocation. Empirical findings which suggest that credit market imperfections are associated with higher child labour (Alvi and Dendir 2011, Cigno and Rosati 2005: 187-207, Guarcello, Mealli and Rosati 2010) should therefore be interpreted with caution. For theoretical work on this topic see Baland and Robinson (2000) and Ranjan (2001).

2008). Based on this argument, microcredit is expected to increase school attendance and reduce child labour. But the studies listed above point to another, opposing effect: If credit is used for investment purposes in the household‘s business, additional productive activities are made available. As a consequence, labour demand increases and so does the marginal product of children‘s work in the family‘s enterprise. Opportunity costs of schooling increase as well. If this effect is dominant, child labour will rise. Hazarika and Sarangi (2008) find empirical evidence for higher child labour due to access to microcredit using cross-sectional data for rural Malawi. Menon (2010) analyses child labour in household‘s non-farm enterprises in Pakistan. The author concludes that investment loans increase the marginal product of labour and opportunity costs of schooling.

Several studies discussed so far point to relative returns to education as an important determinant of child labour. Child time allocation is seen as one decision-making process in which both child labour and school attendance are defined. The decision is based on a trade-off between additional income today (child labour) and higher earnings tomorrow (school attendance). Child labour comes at cost of lower earnings potential in the future (Beegle, Dehejia and Gatti 2006). Relative returns to education are therefore particularly affected by earning opportunities in the labour market available to the child as well as by a child‘s productivity in the family business (Edmonds 2008). Cost of schooling or school quality influence relative returns to education as well. Empirical studies such as Edmonds and Shrestha (2014) support the link between child labour decisions and the return to education. But attending school and doing market or domestic work are not mutually exclusive options (Ravallion and Wodon 2000). Many children in LIC do both.

The discussion shows that a child‘s marginal product of labour in certain activities influences child labour decisions. This idea can be linked to shocks. Cameron and Worswick (2003) argue that a crop loss lowers the marginal product of family farm work. Household members then spend less time working on the farm and more time working off the farm. Even though the study does not particularly look at children‘s work, the authors‘ argument can be applied to children as well: If the child‘s lower marginal product of labour is the dominant impact caused by the shock, child labour will decrease (argument II).

By studying the impact of exogenous shocks to local economic activity in Brazil‘s coffee producing regions, Soares, Kruger and Berthelon (2012) particularly discuss the effect an agricultural shock has on a child‘s opportunity costs of time. With the help of panel data they estimate that a large positive production shock significantly raises the probability that children only work (and not attend school) by +1.2 %. The authors argue that the increase is driven by higher opportunity costs of children‘s time due to higher economic activity. Vice versa, their findings suggest that negative production shocks would decrease child labour (argument II).

Soares, Kruger and Berthelon (2012) distinguish between long-term income changes and short-term income fluctuations. While higher permanent income lowers child labour and increases schooling (income effect), positive economic shocks cause temporary income fluctuations that can increase child labour, as they raise labour demand and opportunity costs of time. Similar to the permanent income hypothesis the distinction identifies the persistence of a shock as an important factor. If the shock only results in a temporary effect, school attendance and labour supply are adjusted only until the household has recovered from the shock (Björkman-Nyqvist 2013). However, children‘s time will not be reallocated again if the shock is permanent.

Cogneau and Jedwab (2012) analyse the effect of an aggregate shock caused by the 1990 cocoa crisis in Côte d'Ivoire. Two effects of negative shocks on child labour are discussed: First, an aggregate shock reduces children‘s opportunity costs of time which lowers child labour. Second, negative shocks cause income fluctuations such that families withdraw children from school and send them to work in order to smooth consumption. Empirical findings suggest the dominance of the latter impact, i.e. argument I. Again, domestic chores are not included. They find that the impact depends on the specification and the sub-sample used: School attendance of young girls is significantly reduced (by 9-11 percentage points) and the economic activity of 12-15-year old boys significantly increased (by 14-16 percentage points).

Cogneau and Jedwab (2012) discuss two other important factors that are related to a child‘s productivity: gender and age. The authors argue that cocoa bean harvesting is a task mainly done by males. It is in line with broad empirical evidence on gender disparities in child labour[9]. In general, girls tend to spend more time on

[9]See Bhalotra and Heady (2003), Björkman-Nyqvist (2013), Dammert (2008), Edmonds (2006) or Landmann and Frölich (2015) for further examples.

domestic chores like cooking or taking care of siblings. Gender differences can also differ across regions and ethnic groups: Beer brewing in Malawi or harvesting plantains in sub-Saharan Africa is mainly done by females (Cogneau and Jedwab 2012, Swaminathan, Salcedo Du Bois and Findeis 2010). The social group of Hima, which lives in South-West Uganda, believes that any contact between women and the cattle results in sickness and death of the cattle (Boholm 2003). Gender-specific tasks are particularly relevant for argument II if shocks affect the marginal product of labour in certain activities. Björkman-Nyqvist (2013) argues that the older children are, the more difficult are the tasks they can perform and the more responsibilities they can take. Following this idea, age becomes an important variable as a child's productivity rises in age.

De Janvry et al. (2006) provide empirical evidence for lower child labour as a response to droughts, although it is only presented as a side effect in the paper. The study focuses on the mitigating impact of Mexico‘s conditional cash transfer programme Progresa on child labour and schooling when households are exposed to shocks. A linear probability model is estimated by using panel data. De Janvry et al. find that the transfer is not sufficient to make households not resort to child labour to smooth consumption. But the negative effect on school enrolment is largely mitigated. Apart from that, very robust estimates indicate that children‘s work participation significantly decreases by about 7.5 percentage points when households experience droughts. De Janvry et al. consider limited opportunities for farm work and more abundant adult labour supply resulting from the drought as a possible explanation. School attendance remains unaffected. No negative relationship is found between child labour and other shocks such as illness or unemployment of the household head.

In summary, there are two main effects that economic shocks can have on child labour. First, economic shocks induce income shocks. Households then need to find a way to smooth consumption. Sending children to work is one strategy that families may apply (argument I). Second, economic shocks affect a child‘s marginal product of labour. Children will work less if the shock limits the efficiency of children‘s work and reduces opportunity costs of time and, consequently, of schooling (argument II). The literature mainly focuses on argument I. There are some studies pointing to the other effect but they mainly focus on different research questions.

3 Microeconomic model

In this section the model of Dillon (2013) is presented as the conceptual foundation of the paper. His theoretical framework has been chosen for several reasons. First, it explicitly models child labour and does not only refer to child labour as the quantification of costs in terms of lost human capital. The number of hours worked by children is particularly taken into account so that a hypothesis at the intensive margin can be derived. Second, the model distinguishes between different types of work and includes time spent on household chores. Third, the conceptual framework can be applied to an agricultural setting where children are mainly engaged in work on the household‘s farm and where economic shocks such as droughts, heavy rains or pest infestations affect income due to crop loss. In particular, Dillon (2013) provides a theoretical set up which helps to understand argument II.

Dillon (2013) develops a two-period household model with an exogenous number of children n.[10] Each child consumes c_1 in period 1 and causes fixed costs for child care b.[11] In period 2 the child earns income y_2 as an adult. Household‘s utility is modelled as the sum of utility derived from adult consumption in period 1 (a_1) and in period 2 (a_2) and from children‘s consumption. Children‘s utility is discounted by β:

$$U = u(a_1, a_2) + \beta n \tilde{U}(c_1, y_2). \tag{1}$$

Households generate profits from market production as well as from home production. Market production includes agricultural production or household businesses and depends on both child labour and adult labour given quasi-fixed input factors capital K and land L.[12] Output prices are denoted by p. Home production is determined by child and adult labour inputs only. Production shocks are modelled as independently and identically distributed (i.i.d.) random shocks δ to the output with $E(\delta) = 1$. Only market production is affected by shocks. Shocks considered here may be insect infestations, severe rainfall or droughts.

Households face budget and time constraints. Children divide their total time T_C among market production ${T_C}^F$, home production ${T_C}^H$, schooling ${T_C}^S$ and leisure ${T_C}^L$.

[10] For more details of the model, see the respective Working Paper Dillon (2008).
[11] Dillon adds costs for schooling. As primary schooling is free in Uganda, school fees do not apply here.
[12] An input is quasi-fixed if it is independent from the specific amount produced. Instead, a fixed quantity of the input is used for any positive output level (Varian 2007: 402).

Adults divide their time among market production ${T_A}^F$, home production ${T_A}^H$, wage labour ${T_A}^W$ and leisure ${T_A}^L$. Time allocation is modelled as a simultaneous decision. If no time is spent on an activity, the corresponding variable is set to zero.

Labour inputs are valued at wage rates representing the opportunity costs of a child‘s and an adult‘s time w_C and w_A, respectively. Superscripts identify types of activities as described above (w^F for market production, w^H for home production, w^W for wage employment). Households can save k in period 1. The budget constraint in period 1 looks as follows[13]:

$$p\delta \cdot q\big(T_A^F, T_C^F | K, L\big) - w_A^F T_A^F - w_C^F T_C^F + h(T_A^H, T_C^A) - w_A^H T_A^H - w_C^H T_C^H + w_A^W T_A^W = a_1 + bn + k. \tag{2}$$

The budget constraint in period 2 restricts the consumption in this period to a_2=rk. Combining all the above yields the following Lagrangian function:

$$\begin{aligned}\max_{\substack{T_C^F, T_C^H, T_C^S,\\ T_A^F, T_A^H, T_A^W,\\ c_1, k}} \mathscr{L} = u[&\underbrace{p\delta \cdot q\big(T_A^F, T_C^F\big) - w_A^F T_A^F - w_C^F T_C^F + h(T_A^H, T_C^A) - w_A^H T_A^H - w_C^H T_C^H + w_A^W T_A^W - bn - k}_{=a_1},\\ &\underbrace{rk}_{=a_2}\,] + \beta n \tilde{U}(c_1, y_2)\\ &+ \lambda_A(T_A - T_A^F - T_A^H - T_A^L - T_A^W)\\ &+ \lambda_C(T_C - T_C^F - T_C^H - T_C^L - T_C^S).\end{aligned} \tag{3}$$

Dillon‘s model is based on some crucial assumptions. First, neither working nor leisure or schooling are arguments of the household‘s preferences themselves. Instead, the different activities are incorporated only as labour inputs to household production. Since leisure and schooling do not directly affect utility but only appear as a residuum in the time constraint, it is not efficient to allocate any time to these activities if the shadow value of children‘s time is represented by wages. If no time is spent on leisure and schooling, argument I can hardly be derived. So, increasing total house-

[13]Dillon (2013) does not include child‘s consumption c_1 in the budget constraint of period 1. The specification can be explained by the three-period model he develops in Dillon (2008). If the decision-making process is split up into three periods, the number of children n is chosen in the first period. In the second period - which basically refers to the first period in Dillon (2013) - the household faces costs of a child‘s schooling and consumption. The child‘s consumption level is not modelled as a choice variable in this period.

hold labour supply as a response to shocks cannot be modelled given this assumption. Second, children cannot work for wages while adults do. Dillon argues that this specification is chosen due to the fact that in Northern Mali, where his study refers to, child wage labour is very rare. Data shows that the situation is similar for Uganda (figure 4 in chapter 4.1). Third, labour markets are modelled as imperfect if different wages are associated with different occupations. Fourth, the production possibility set must be defined over the non-negative range *ex post*. In case of a shock which completely destroys the harvest the production possibility set is zero. As a consequence, the marginal product of child labour goes to zero (Dillon 2013).

The first order conditions of interest are:

$$\frac{\partial \mathscr{L}}{\partial T_C^F} \stackrel{!}{=} 0 \quad \longleftrightarrow \quad \frac{\partial u}{\partial a_1} p\delta \cdot \frac{\partial q}{\partial T_C^F} = \frac{\partial u}{\partial a_1} w_C^F + \lambda_C. \tag{4}$$

$$\frac{\partial \mathscr{L}}{\partial T_C^H} \stackrel{!}{=} 0 \quad \longleftrightarrow \quad \frac{\partial u}{\partial a_1} \cdot \frac{\partial h}{\partial T_C^H} = \frac{\partial u}{\partial a_1} w_C^H + \lambda_C. \tag{5}$$

Equation (4) describes the equilibrium condition for market production as far as the child is concerned. Adult‘s marginal utility of adding one unit of child labour to market production must be equal to the sum of the shadow value of the child‘s time and the increase in adult‘s marginal utility from the return on child‘s time in market production (Dillon 2008). The right hand side quantifies the opportunity costs of adding one more unit of child labour to market production. Equation (5) can be interpreted equivalently. To analyse the impact of a production shock on child labour Dillon assumes Cobb-Douglas production functions for both market and home production:

$$q = \left(T_A^F\right)^{\alpha} \cdot \left(T_C^F\right)^{1-\alpha} \qquad (0 < \alpha < 1) \tag{6}$$

$$h = \left(T_A^H\right)^{\alpha} \cdot \left(T_C^H\right)^{1-\alpha} \qquad (0 < \alpha < 1). \tag{7}$$

Deriving the marginal product of child labour $\frac{\partial q}{\partial T_C^F}$ and $\frac{\partial h}{\partial T_C^H}$, plugging it into equation (4) and (5) and solving for child labour yields:

$$T_C^F = \left(\frac{\frac{\lambda_C}{\frac{\partial u}{\partial a_1}} + w_C^F}{p\delta \cdot (1-\alpha)\left(T_A^F\right)^{\alpha}} \right)^{-\frac{1}{\alpha}} \tag{8}$$

$$T_C^H = \left(\frac{\frac{\lambda_C}{\frac{\partial u}{\partial a_1}} + w_C^H}{(1-\alpha)\left(T_A^H\right)^\alpha} \right)^{-\frac{1}{\alpha}} . \tag{9}$$

Comparative statics shows the changes in child labour the model predicts *ceteris paribus* for non-zero adult labour supply if a positive economic shock occurs:

$$\frac{\partial T_C^F}{\partial \delta} = \underbrace{\frac{1}{\alpha}}_{>0} \cdot \underbrace{\left(\frac{\frac{\lambda_C}{\frac{\partial u}{\partial a_1}} + w_C^F}{p(1-\alpha)\left(T_A^F\right)^\alpha} \right)^{-\frac{1}{\alpha}}}_{>0} \underbrace{\cdot (\delta)^{\frac{1}{\alpha}-1}}_{>0} . \tag{10}$$

The model predicts that children increase labour supply in market production as a response to positive production shocks. Therefore, child‘s time spent on market production is supposed to decrease if a negative production shock occurs[14]. From a microeconomic perspective the decrease in child labour is driven by the lower marginal product of labour in this activity due to the shock. A household would transfer children‘s time from market production to home production, other things being equal.

However, analysing the impact of a production shock becomes a lot more complex if intra-household substitution of labour and other technologies are considered as well. As shown in equation (10), the shadow value of children‘s time as well as adult labour in market production matters. As a result of the negative production shock, the marginal product of labour in market production decreases. Labour supply will be shifted towards home production up to a point where the marginal product in both activities is balanced again. But it is not only one person who adjusts labour supply but both adults and children. Children and adult time is allocated in a simultaneous decision-making process. Dillon (2013) argues that substitution between adult and child labour may mitigate the magnitude by which children adjust the time they spend on market production. Furthermore, he notes that the impact of production shocks on children‘s work in home production depends on changes in the shadow value of children‘s time λ_C. λ_C is determined by the household‘s child and adult labour availability, but also by the relative productivity of each type of labour (Dillon 2013).

[14]Dillon (2013) concludes that child labour in market production increases as a response to negative production shocks. Mathematically and intuitively the effect derived here seems appropriate.

The author leaves the effect of shocks to market production on child labour at home as an open question that needs to be answered empirically.

The extent to which adult labour and child labour can be substituted is defined by the production technology. In Cobb-Douglas production functions inputs are imperfect substitutes. Both factors are necessary to produce non-zero output. Under the conditions of ignoring adult wage employment and differences in wages for different occupations, children and adults will decrease their time spent on market production and shift labour to home production if a negative production shock occurs. This can be seen by the numerical example provided in appendix A. The decision-making process is reduced to a one-period profit maximization problem where income is only generated by market and home production specified by Cobb-Douglas production technology. The share of output earned by adult labour is assumed to be higher than the share of output earned by child labour in both technologies, but the difference is greater for market production. This assumption is indicated by the exponents in the production functions. Based on this set up, the marginal product of adult and child labour in market production decreases in case of a negative production shock. Consequently, all household members spend more time on home production in the new equilibrium. In absolute terms, adults spend more time on market production than children do before and after the shock. For home production it is the children who work more in this activity.

But under less restrictive assumptions there may be another effect pushing child labour in the opposite direction. Dillon (2008) mentions that the marginal value of a child‘s labour input raises if less labour is allocated to a production process in total: As a response to negative shocks, adults shift time they used to spend on market production towards other income generating activities like wage labour. With adults working less in market production, child labour in this activity may now be more valuable from a microeconomic perspective. Thus, children‘s work in market production increases. Whether or not this effect is dominant depends on the rate by which adult and child labour can be substituted in market and home production, among others.

For instance, perfect substitutes may trigger different labour supply adjustments if households experience negative production shocks. Production technology that combines two inputs as perfect substitutes usually leads to corner solutions. The input factor that is relatively cheaper is used. Its costs are measured by opportunity costs of time in this case. Only if their ratio is equal to the ratio by which both inputs can be substituted in the production, any pair of adult and child labour supply is efficient. If the shock affects opportunity costs of time such that the (in-)equality sign between these rates turn, market production may be based on child labour only.

So theoretical predictions on how households adjust labour supply are ambiguous if different production technologies and activities are considered. As a direct impact, production shocks decrease the marginal product of child labour in market production, which makes increasing the time of working on home production more attractive instead. Yet under certain circumstances there may be another, indirect effect on child labour which pushes children‘s time back to market production. This special case occurs if production technologies and wages allow for children compensating the reduced time adults now spend on market production, since their marginal product of labour in market production has dropped as well because of the shock.

In summary, under strict assumptions the model predicts that child labour in market production such as on-farm work decreases as a response to negative production shocks, other things being equal. This finding corresponds to argument II derived in chapter 2. The underlying hypothesis of argument II will be tested empirically by looking at child labour in Uganda. Dillon‘s (2013) model does not provide clear predictions in terms of intra-household substitution of labour supply and interrelated effects.

4 Empirical analysis

4.1 Contextualisation

Uganda is a landlocked country in East Africa which has one of the youngest and fastest growing populations in the world. More than 80 % of Uganda‘s 35 m. inhabitants live in rural areas (UBOS and UCW 2014). The majority of Ugandans are Christians but there is also a sizeable Muslim minority (Peterman et al. 2011). With a Gross National Income (GNI) of $ 600 per capita in 2013 Uganda is classified as a LIC according to the standard definition[15] (World Bank 2015). After more than 20 years of civil war the Northern part still recovers from the consequences of the conflict between the government and the Lord’s Resistance Army (LRA) which caused vast internal displacement and disruption of family structures (Adams, Salazar and Lundgren 2013).

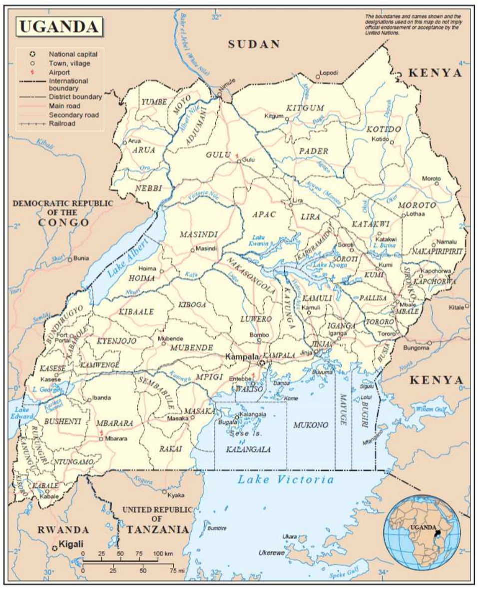

Figure 1. Map of Uganda
Source: UN 2003.

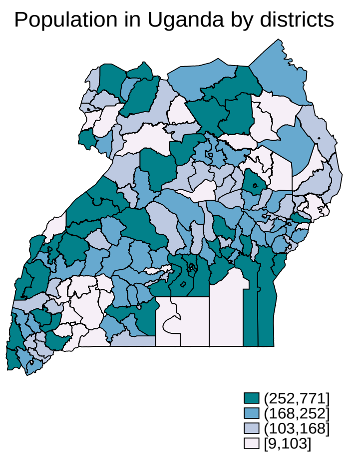

Figure 2. Population by districts in thousands
Source: own creation based on FSP 2013.

While Uganda‘s main export product coffee is mostly cultivated by large-scale farmers (Peterman et al. 2011), small-scale subsistence farming is very common in rural areas. Tubers, plantains, grains and beans are grown for own consumption and for sale. According to the UNPS sample, the families of about 60 % of children living rural areas mainly rely on farm-related income (Figure 3).

[15]The World Bank defines a country as a LIC if its GNI per capita is $ 1,045 or less.

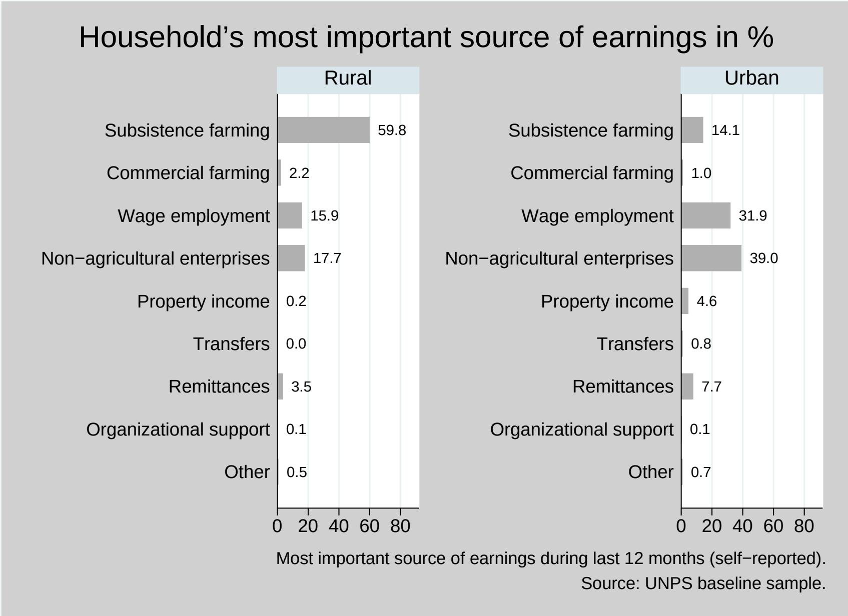

Figure 3. Households' most important income source by area

Uganda's agricultural sector is mainly rain-fed (Björkman-Nyqvist 2013). This is why farmers' output and income highly depend on weather conditions. There are two rainy seasons, which is from March to June and from October/November to December/January. According to official reports, season patterns have recently become less predictable which negatively affects agricultural output (Republic of Uganda 2010). Table 18 in appendix B illustrates the incidence of different agricultural shocks in the UNPS sample. Focusing on droughts, table 1 shows that per wave between 27 % and 52 % of children in the sample live in households that were affected by droughts. Incidence varies across waves.

Table 1. Droughts by wave

	Wave of Panel							
Experienced drought	**1**		**2**		**3**		**Total**	
	No.	Col %	No.	Col %	No.	Col %	No.	Col %
No	1442	47.7	3071	72.8	422	68.6	4934	62.8
Yes	1580	52.3	1149	27.2	193	31.4	2922	37.2
Total	3021	100.0	4219	100.0	615	100.0	7856	100.0

Data source: UNPS. Droughts experienced by households during the last 12 months, self-reported.

Baseline sample includes children aged 6-13 who were interviewed at least twice. Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Observations are weighted based on the sampling design.

In 1997, the government removed school fees for primary education for up to two boys and two girls for each family (Wells 2009). After this policy had been implemented, enrolment rates increased considerably. Table 2 shows the enrolment status of children in the sample. 87 % of children aged 6-13 stated to currently attend school. School attendance is lower in rural areas and among boys. Both findings are confirmed by other surveys, but the UNPS suggests slightly lower enrolment rates (UBOS and UCW 2014). Primary schooling in Uganda usually starts at the age of 6 and ends at the age of 13, but children are often not enrolled at the appropriate age (Wells 2009). This finding will be taken into account by robustness checks with varying age range.

Table 2. School attendance by gender and area

	Urban/Rural Identifier		
Gender	**Rural**	**Urban**	**Total**
	%	%	%
Female	0.89	0.91	0.89
Male	0.85	0.94	0.86
Total	0.87	0.93	0.87

Data source: UNPS.

Baseline sample includes children aged 6-13 who were interviewed at least twice.

Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Observations are weighted based on the sampling design.

Even though the data does not suggest any gender disparities in favour of boys, some comments on gender issues are worth being added here. Gender inequality has decreased in primary school in recent years, but secondary schooling and primary completion rates are still lower for girls. In general, local gender norms highlight men‘s power and social position and have been manifested in Uganda‘s educational system, labour market as well as in its land laws (UBOS and UCW 2014).

Child labour is widespread. The minimum age for work in Uganda is 14. Children aged 12 or 13 are already allowed to carry out light work when supervised by an adult (UBOS and UCW 2014). Nevertheless 39 % of children aged 6-13 are engaged in market work in the baseline sample (see Table 3). Boys are more likely to work.

The data supports the finding of different working patterns in rural and urban areas that have been mentioned in chapter 2. Only 15 % of children in urban areas are

Table 3. Market work by gender and area (extensive margin)

	Urban/Rural Identifier		
Gender	**Rural**	**Urban**	**Total**
	%	%	%
Female	0.39	0.13	0.37
Male	0.44	0.16	0.41
Total	0.42	0.15	0.39

Data source: UNPS. Market work includes paid work, work as an apprentice, work for household business or household farm.
Baseline sample includes children aged 6-13 who were interviewed at least twice.
Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Observations are weighted based on the sampling design.

engaged in market work, compared to 42 % in rural areas. 96 % of working children in rural areas whose employment status is known stated to work on the household farm or with household livestock (Figure 4). And even in urban areas the corresponding figure is 74 % resulting from the fact that agriculture is still important in the informal economy of urban areas (UBOS and UCW 2014).

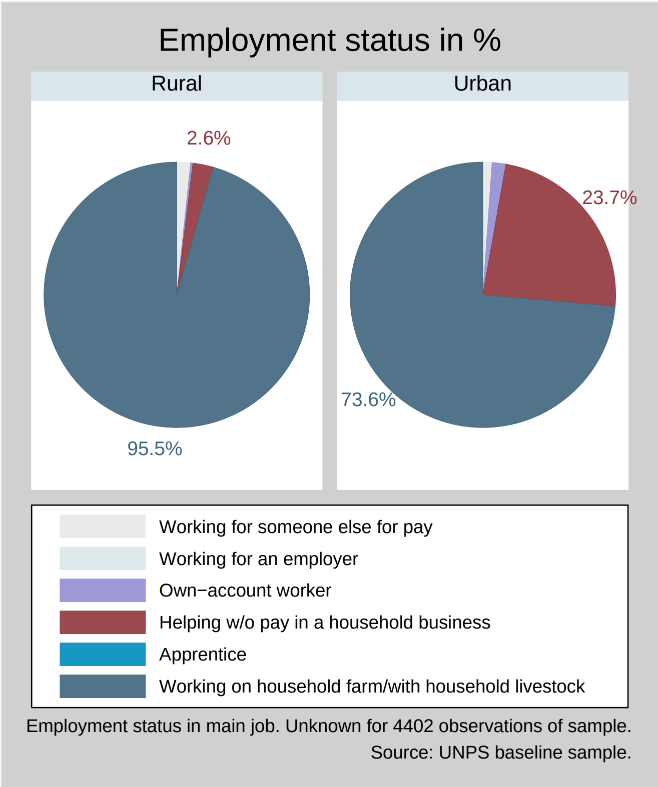

Figure 4. Children's employment status by area

As discussed above, children‘s market work is only part of the story. Non-market labour activities like domestic chores are relevant as well. Table 4 shows that children in Uganda who are engaged in these types of work mainly fetch water, collect firewood or help on the household‘s farm. Data at the intensive margin is presented conditional on non-zero hours worked in non-market activities. On average these children spend 1.6 hours a week on collecting firewood, 5 hours on fetching water and 3.5 hours on agricultural work. Boys are more engaged in farm work, while girls spend more time on fetching water. This finding is in line with other studies on Uganda. Björkman-Nyqvist (2013) argues that in Uganda girls are seen as more productive in household chores such as cleaning, fetching water or taking care of siblings compared to boys. On average children spend hardly any time on construction, repairs, processing food, handicraft and fishing. Additional measures on child labour are shown in the main summary statistics of table 8. High standard deviations indicate a relatively high spread around the mean of children‘s work in different activities within the sample[16].

Table 4. Non-market work by gender (intensive margin)

	Mean hours worked		
	Female	**Male**	**Total**
Collecting firewood	1.84	1.28	1.57
Fetching water	5.25	4.64	4.95
Agriculture	3.04	4.03	3.52
Construction	0.01	0.03	0.02
Repairs	0.00	0.01	0.01
Processing food	0.12	0.02	0.07
Handicraft	0.03	0.01	0.02
Fishing	0.02	0.11	0.07

Source: UNPS. Conditional hours worked in non-market labour activities in the last 7 days. Baseline sample includes children aged 6-13 who were interviewed at least twice. Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Observations are weighted based on the sampling design.

Table 5 shows the mean hours children in the UNPS base sample spend on market and non-market work conditional on non-zero working hours in the respective activ-

[16] Descriptive statistics presented in other studies point to dispersed child labour data as well (Bhalotra and Heady 2003, Beegle, Dehejia and Gatti 2006, Dillon 2013).

Table 5. Market and non-market work (intensive margin)

	Mean hours worked	
	Market work	**Nonmarket work**
Gender		
Female	9.79	10.33
Male	11.31	10.14
Total	10.60	10.24
Urban/Rural Identifier		
Rural	10.57	10.55
Urban	11.37	6.29
Total	10.60	10.24
School attendance		
No	24.76	8.75
Yes	9.72	10.37
Total	10.60	10.24
Highest level of father's education completed		
No formal education	15.29	11.35
Less than Primary	9.92	10.19
Completed Primary	9.98	9.98
Completed O-Level	9.33	8.83
Completed A-Level	11.78	10.89
Completed University	11.03	11.05
Other (Specify)	11.00	11.59
Total	10.53	10.17
5 quantiles of land holdings		
1	12.50	10.85
2	10.93	10.82
3	9.95	10.36
4	9.54	9.92
5	10.78	8.98
Total	10.59	10.24

Data source: UNPS. Conditional hours worked in market and non-market labour activities in the last 7 days. Data on father's education is unknown for 955 observations of the baseline sample, data on land quintile is unknown for 47 observations, so total hours slightly differ in these sections.
Baseline sample includes children aged 6-13 who were interviewed at least twice. Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Observations are weighted based on the sampling design.

ity[17]. On average economically active children work 10.6 hours a week. The figure is quite similar for conditional hours of non-market labour activities. Note that these figures cannot simply be added up, since the survey asks for agricultural work in the section of market activities as well as in the section of non-market labour activities. However, the clear distinction made by the interviewees can be questioned here.

There is almost no difference in the mean hours boys and girls spend on non-market labour activities (table 5). But there are gender disparities regarding market work. In these types of work, boys work on average 1.5 hours a week more than girls.

The data indicates considerable differences between working children in urban and rural areas. Children in rural areas who help at home spend almost twice the time on non-market work (10.6 hours) than child labourers in urban areas. The finding seems to be related to labour-intensive on-farm work which is what most child labourers in Uganda‘s rural areas are involved in (figure 4). However, while children in rural areas are more likely to be engaged in market work (extensive margin, table 3), working children in urban areas spend slightly more time on market activities.

Since table 5 only refers to children who do spend time on market and/or non-market work, it includes children who either do both, attend school and work, or who exclusively work. The data supports the idea that many children in LIC do both. On average pupils even spend more hours on non-market labour activities than working children who do not attend school. The opposite holds for market work and differences are quite large in absolute terms: Working pupils spend 9.7 hours per week on market work. Child labourers that do not go to school work 24.8 hours a week on average. These figures fit quite well to other data on Uganda (UBOS and UCW 2014).

As expected, children whose father has no formal education work the most in the base sample. Children work on average fewer hours in non-market labour activities if the household‘s relative land holdings rise, but differences are rather small in absolute terms. Children of landless families, i.e. households belonging to the first land holding quantile, spend more time on market work (12.5 hours) than children in land-rich households. As discussed in chapter 2, land holdings are associated with wealth but they may also increase a child‘s productivity to work on the farm. The UNPS rather supports the wealth argument. Yet rented land is not considered in these figures.

[17]For unconditional figures see table 20 and table 22 in appendix B.

The survey includes self-reported information on how households cope with shocks. With regard to the research question of this paper, a closer look at these strategies is useful. Table 6 lists coping strategies of households as response to droughts.

Table 6. Households‘ coping strategies in case of droughts by land holding quintiles

	5 quantiles of land holdings					
Main response to drought	**1**	**2**	**3**	**4**	**5**	**Total**
	Col %	Col %	Col %	Col %	Col %	Col %
Unconditional help of relatives/friends	27.1	7.5	5.7	11.5	6.2	11.2
Unconditional help of local gov.	0.4	1.3	0.6	0.2	0.6	0.7
Changed dietary patterns involuntarily	20.7	36.9	27.7	32.9	24.4	29.8
Changed cropping practices	13.7	3.3	4.6	3.1	14.1	6.9
Took on more non-farm employment	15.6	10.9	8.8	9.9	6.1	10.4
Took on more farm wage employment	1.5	6.9	2.8	3.7	1.8	3.8
HH member(s) migrated	0.5	0.0	0.0	1.2	0.0	0.3
Relied on savings	10.5	23.8	30.3	26.0	35.3	24.9
Obtained credit	0.3	0.8	4.0	0.5	0.4	1.1
Sold durable HH assets	0.8	0.6	0.7	3.2	1.1	1.3
Sold land/building	0.0	0.5	0.0	0.0	0.0	0.1
Rented out land/building	0.2	0.0	0.0	0.0	0.2	0.1
Distress sales of animal stock	1.4	1.2	1.3	0.8	1.5	1.2
Sent children to live elsewhere	0.9	0.0	0.0	0.0	0.0	0.2
Reduced health/educat. expenditures	1.6	0.3	0.1	0.8	1.7	0.8
Other	4.8	6.0	13.4	6.2	6.4	7.1
Total	100.0	100.0	100.0	100.0	100.0	100.0

Data source: UNPS. Household‘s strategies to cope with droughts, self-reported.

Data on coping strategies is unknown for 26 observations of the baseline sample who experienced a drought.

Baseline sample includes children aged 6-13 who were interviewed at least twice. Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Observations are weighted based on the sampling design.

Changing dietary patterns is the most common response (30 %). Households try to reduce expenditures by consuming less or cheaper food. Since subsistence farming is widespread, droughts could destroy the harvest such that farm households cannot consume the crops they cultivated. Changing dietary patterns is least prevalent among households belonging to the lowest land holding quintile, i.e. the landless. Table 19 in appendix B illustrates some details on this quantile. Landless families are not necessarily poor. They make up one fourth of observations in the highest consumption quantile. Rich urban households drive this figure, for example.

25 % of children live in households that state to have relied on savings when hit by a drought. The fact that almost no household rents out land confirms the assumption in the conceptual framework that excludes rents or prices for land. It is worth noting that while many households make use of savings to smooth consumption in case of a drought, only a negligible share states to have sold assets, buildings, land or animal stock. So the self-reported data does not support the buffer stock interpretation of assets discussed in Beegle, Dehejia and Gatti (2006). Only 1 % of children live in households that obtained credit as a response to a drought. This is not surprising given the fact that formal borrowing is not very common in LIC. Similar to other countries in sub-Saharan Africa financial institutions in Uganda are rarely located in rural areas where the majority of the population lives (Kiiza and Pederson 2001).

Despite the covariate nature of droughts informal arrangements seem to be available. 11 % in total and 27 % of the landless state to have received unconditional help of relatives or friends. Additionally, special informal insurance arrangements have been established in Uganda. *Nigiina* associations in rural and peri-urban areas can be seen as one of them. *Nigiina* associations are informal gift giving associations whose members are predominantly poor women working in the informal sector (Nakirya and State 2013). They may explain part of the strategies summarised as "Other".

For this study adjustments in labour supply are particularly interesting. Off-farm labour supply is an important diversification strategy to maintain food security, among others, when peasant households are hit by income shocks (Swaminathan, Salcedo Du Bois and Findeis 2010). Among those who were hit by a drought 10 % report that at least one family member took on more non-farm work. The figure is considerably higher for the landless (16 %). Although they do not own land, farming activities are restricted by droughts as well if they rent land. Only few households increased farm wage employment. This seems reasonable given the covariate nature of droughts, the lower marginal product of farm work and imperfect labour markets in rural Uganda.

Increasing household labour suggests that the drought caused income fluctuations so that additional income had to be generated in order to smooth consumption. This data does not reveal whether it is the children who work more. Descriptive data presented in table 7 shows that the mean of hours children work is higher for those whose families state to have experienced a drought. But given that the relationship is complex, the explanatory power of these descriptive findings is limited. The empirical analysis will shed more light on it by using FE regression techniques. Main summary statistics for the full sample are depicted in table 8. A full list of variable names and labels is provided in appendix B (table 23). Sampling and data issues related to the third wave will be discussed in the next chapter.

Table 7. Summary statistics by shock and wave

	Drought		*Wave*		
	Yes	**No**	**1**	**2**	**3**
hours_job	4.55	3.86	4.09	3.40	9.17
hours_nonmarket	8.03	7.23	7.18	6.89	13.61
fetch_wood	1.42	1.00	1.24	1.01	1.73
fetch_water	3.71	3.60	3.28	3.67	5.22
agriculture	2.68	2.54	2.52	2.06	6.52
construction	0.01	0.02	0.03	0.01	0.00
repairs	0.01	0.00	0.01	0.00	0.00
process_food	0.06	0.05	0.04	0.06	0.07
handicraft	0.03	0.01	0.03	0.01	0.00
fishing	0.11	0.01	0.02	0.07	0.06
schooling	0.85	0.89	0.87	0.87	0.96
HH_no	8.95	8.36	8.52	8.49	9.49
age	9.56	9.61	9.52	9.46	10.81
cons (ln)	10.53	10.55	10.68	10.45	10.43
land (ln)	12.57	12.99	12.66	12.89	13.32

Data source: UNPS. Monthly household consumption expenditures (cons (ln)) and estimated value of land holdings (land (ln)) are described in logarithms.
Baseline sample includes children aged 6-13 which were interviewed at least twice.
Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Observations are weighted based on the sampling design.

Table 8. Summary statistics

	Mean	St. Dev.	Min	Max	N
age	9.59	2.31	6	13	7856
sex	0.50	0.50	0	1	7856
schooling	0.87	0.33	0	1	7856
hours_job	4.12	8.66	0	106	7856
hours_nonmarket	7.53	9.78	0	162	7856
fetch_wood	1.15	2.10	0	30	7856
fetch_water	3.64	4.80	0	95	7856
construction	0.02	0.49	0	24	7856
repairs	0.00	0.12	0	5	7856
process_food	0.05	0.64	0	18	7856
handicraft	0.02	0.48	0	50	7856
agriculture	2.59	6.59	0	150	7856
fishing	0.05	1.23	0	56	7856
job_d	0.39	0.49	0	1	7856
nonmarket_d	0.74	0.44	0	1	7856
fetch_wood_d	0.38	0.48	0	1	7856
fetch_water_d	0.68	0.47	0	1	7856
construction_d	0.00	0.05	0	1	7856
repairs_d	0.00	0.04	0	1	7856
process_food_d	0.01	0.12	0	1	7856
handicraft_d	0.00	0.05	0	1	7856
agriculture_d	0.28	0.45	0	1	7856
fishing_d	0.00	0.07	0	1	7856
HH_no	8.58	3.72	1	29	7856
urban	0.10	0.30	0	1	7856
cons (ln)	10.54	0.72	8.13	18.65	7849
land (ln)	12.84	5.66	0.00	21.72	7809
drought	0.37	0.48	0	1	7856
floods	0.03	0.17	0	1	7856
pest	0.04	0.19	0	1	7856
season	0.51	0.50	0	1	7856

Data source: UNPS. Data on consumption is unknown for 7 observations of the baseline sample, data on land is unknown for 47 observations. Land and consumption are not included in the regression analysis.

Baseline sample includes children aged 6-13 which were interviewed at least twice. Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Observations are weighted based on the sampling design.

4.2 Data and variables

The empirical analysis is based on panel data of the UNPS 2009/10, 2010/11 and 2011/12. The survey was implemented by the Uganda Bureau of Statistics (UBOS) with financial and technical support of the World Bank‘s LSMS project (UBOS 2010). The LSMS project provides assistance with collecting survey data that is comparable across countries (Deaton 1997: 33). Raw data is available on the World Bank website.

The UNPS is a multipurpose household survey with three different questionnaires for households, communities and agriculture. The survey is conducted annually over a twelve month period. Each household is visited twice a year to better capture the impact of Uganda‘s two cropping seasons. However, the full interview is not conducted twice. Sections on employment, shocks, household composition and consumption which are most relevant for this analysis are only asked once a year.

The survey is based on a nationally representative sample of households (UBOS 2010). The UNPS was carried out as a new survey but its sample is a sub-sample of the Uganda National Household Survey (UNHS) 2005/06. In order to select the Enumeration Area (EA)s as primary sampling units in the UNPS 2009/10, the UNHS sample was divided into five regional strata. EA codes refer to communities. Within each stratum EAs were selected based on random sampling. All households in this randomly selected sub-sample of the 2005/06 survey are included in the 2009/10 survey. In each EA two of these households were randomly selected as split-offs tracking targets. Their members were tracked and reinterviewed in case they split off from their original sample households (UBOS 2010). In the 2009/10 sample there are no more than 10 households per EA. The maximal number of households per community is rising across the two consecutive waves due to families that split off or moved. Sampling weights account for the complex sampling structure. For details on the calculation of these weights see UBOS (2010).

3,123 households of the 7,400 households in the UNHS sample were selected to be reinterviewed (UBOS 2006, UBOS 2010). Due to attrition, there are 2,975 households distributed over 318 EAs in the final sample of the first wave 2009/10, 2,714 households distributed over 324 EAs in the final sample of the second wave 2010/11 and 2,847 households distributed over 321 EAs in the final sample of the third wave 2011/12. The resulting panel includes 13,820 observations of children aged 6-13. The upper bound of the age range is determined by the age of completed primary schooling in Uganda. Many child labour studies use this reference age to define their samples (Beegle, Dehejia and Gatti 2006).

The data cleaning process reduced the sample considerably. For many individuals information on their age is missing. In order to study child labour, knowing the age is crucial. This is why different procedures have been applied to filter age data out of other information. Additional age data was derived from other waves (+/-1, respectively) or from reported date of birth if available. Implausible age differences across waves such as individuals stating the same age in each survey round were adjusted as far as possible. Although the section on labour force status is supposed to be applied to any household member who is 5 years or above, information on hours worked is missing for several children in the dataset. For some children relevant information on the household level such as shock incidence or community code are missing as well. Data quality may vary for different interviewers. Because of missing data on the interviewer this presumption could not be checked in the data either.

Table 9. Children‘s attrition by wave

	Wave of Panel			
Waves per individual	**1**	**2**	**3**	**Total**
	Col %	Col %	Col %	Col %
1	7.4	3.5	22.3	11.0
2	9.2	12.9	12.4	11.6
3	83.4	83.6	65.4	77.4
Total	100.0	100.0	100.0	100.0

Data source: UNPS. Number of waves in which children were interviewed.
Sample consists of all children aged 6-13 including those who have missing information on other variables. Observations are weighted based on the sampling design.

Table 9 shows how often children of the appropriate age were interviewed. 77 % of them are part of all three waves as expected. 11 % appear only once so that they are excluded from the panel analysis. Attrition varies across waves. In the third wave 22 % of children interviewed in this survey round are singletons. However, the information documents provided by UBOS do not give an explanation for that fact. Table 24 in appendix B shows that in the last survey round 30 % of households are added to the sample. Households are coded as recently added households also if their members have been part of earlier survey rounds but split off from their original families.

It is also the third wave in which information on working patterns is missing most frequently. This is another reason why the number of observations from the last survey round is considerably lower (table 10). Moreover, mean hours children work are higher in this wave, especially in agriculture (table 7). The latter table also shows that in wave 3 children are on average older than in wave 1 and 2, they attend school more often and live in larger families. As part of chapter 4.5, these difficulties are addressed by a robustness check that excludes wave 3. Chapter 4.6 discusses related issues like attrition.

Table 10. Children's work by wave

	Mean hours worked			
Wave of Panel	**Market work**	**Nonmarket work**	**Agriculture**	N
1	4.09	7.18	2.52	3,437
2	3.40	6.89	2.06	3,684
3	9.17	13.61	6.52	735
Total	4.12	7.53	2.59	7,856

Data source: UNPS. Hours worked in market and nonmarket labour activities in the last 7 days.
Baseline sample includes children aged 6-13 who were interviewed at least twice. Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Observations are weighted based on the sampling design.

The base sample is an unbalanced panel including 7,856 observations. Information on hours worked refer to the last week. The variable labelled *hours_job* indicates how many hours individuals worked on market labour activities in their main and second job. Such activities include work for salary or any payment in kind, paid domestic work, running a business or working in a household‘s business, working as an apprentice or on the household‘s farm. Time spent on non-market labour activities is reported by the variable *hours_nonmarket*. It is the sum of hours children spent on collecting firewood, fetching water, making major repairs to their dwellings, processing food, making handicrafts for household use, fishing and hunting as well as agriculture. Time spent on each of them, respectively, is also known. Non-zero hours worked by a child in different activities are denoted by dummies[18]. These dummies represent a child‘s work participation in different types of work.

In this paper the term non-market labour activities will be used for two reasons. First, as explained above, domestic work as an alternative definition is not appropriate given the fact that several activities are not done at home. Second, non-market labour activities is what the UNPS questionnaire refers to. The framework in which the questions were asked will be applied to this analysis.

According to the structure of the questionnaire, farm work may be included in both *hours_job* and *hours_nonmarket*. Distinguishing between on-farm hours that refer to economic activity on the one hand and on-farm hours that should rather be defined as non-market labour activity on the other hand is hardly possible. Beegle, Dehejia and Gatti (2006) point to the same problem. The following empirical analysis deals with it by separately using *hours_job*, *hours_nonmarket* and *agriculture* as dependent variables. It seems the most reasonable way to disentangle on-farm hours, even though it does not imply a complete isolation of agricultural work.

Current school attendance is described by the binary variable *schooling*. Shocks are measured as binary variables at the household level. The economic shock is measured by droughts experienced by households in the last 12 months (*drought*). The alternative indicators *pest* and *floods* refer to floods and crop pests experienced by households in the last 12 months. All shocks are self-reported.

[18]Respective work participation is denoted by *job_d*, *nonmarket_d*, *fetch_wood_d*, *fetch_water_d*, *construction_d*, *repairs_d*, *process_food_d*, *handicraft_d*, *agriculture_d* and *fishing_d*

4.3 Empirical approach

This paper examines the impact of economic shocks on child labour. The empirical approach is closely related to Beegle, Dehejia and Gatti (2006) and incorporates theoretical considerations derived from the conceptual framework described in chapter 3. The basic regression specification looks as follows:

$$y_{ijt} = \beta_0 + \beta_1 X_{ijt} + \beta_2 shock_{ijt} + \epsilon_{ijt}, \tag{11}$$

where subscript i refers to individuals, j to households and t to waves (t=*1,2,3*). On the left hand side the dependent variable y represents child labour in hours for different activities. On the right hand side X represents a set of control variables. The independent variable *shock* is a dummy indicating the economic shock and ϵ is the error term. The coefficient of interest is β_2. Based on the theoretical model, $\beta_2 < 0$ (argument II) is expected for child labour in market labour activities and on the farm. The model is estimated by Ordinary Least Squares (OLS). Similar to the reference paper the sample is not restricted to children who work. It includes all children belonging to the age group for whom necessary data is available.

As discussed in the literature review, the relationship is likely to be affected by various other factors like family living standards, household assets, a household‘s agricultural production technology, access to credit or social networks and others. Many of them are unobserved and are difficult to include in the model. If one or more of these variables is a determinant of the dependent variable child labour and correlated with the shock, omitted variable bias will be a concern (Stock and Watson 2012: 810). Estimates that do not control for unobserved heterogeneity are biased. However, panel data allows for controlling for some omitted variables even if they are unobserved.

FE are applied here to eliminate time-invariant unobserved heterogeneity between households. For the identification of the model, within variation is used. Household FE take into account that the main independent variable, i.e. the shock, varies at the household level. Beegle, Dehejia and Gatti (2006) stress that using household FE also means to focus on the idiosyncratic component of the shock. Clustered standard errors are used to allow for heteroscedasticity and arbitrary autocorrelation within a household. Errors are treated as uncorrelated across entities.

While FE regression models are able to control for time-invariant household characteristics, factors that vary over time remain a concern if they are not included in the model. Beegle, Dehejia and Gatti (2006) argue that this problem will arise, for instance, if shocks to the production technology at the community level occur or if the availability of schools changes. To cope with some of these issues, community-time dummies are included as well. To be able to estimate the model, only community-wave clusters are used that contain at least 5 observations. For varying samples used as robustness checks this requirement is adjusted to the new samples. Community-time dummies do not provide additional information if all they can explain is already captured by other FE. A robustness check in chapter 4.5 will take a closer look at it.

Following Beegle, Dehejia and Gatti (2006), a dummy is included indicating whether the household was interviewed during the rain season. Child labour is measured by hours worked in the last week such that the timing of the interview may matter. Dummies for each wave are included as well. Wave dummies represent time fixed effects that control for variables which change over time but are constant across all households (Stock and Watson 2012: 400). Fluctuating macroeconomic conditions like inflation (figure 5) affecting the whole country are captured by wave dummies. Based on Beegle, Dehejia and Gatti (2006), the following model will be estimated:

$$y_{ijkst} = \alpha_j + \eta_t + \gamma_s + \mu_{kt} + \beta_0 + \beta_1 X_{ijkst} + \beta_2 shock_{ijkst} + \epsilon_{ijkst}, \qquad (12)$$

where α_j denotes household FE, η_t denotes survey round FE, γ_s is the season dummy and μ_{kt} represents community-time FE. Due to additional FE further indices - s for season and k for community - are included. The empirical approach takes into account the complex sampling structure by including sampling weights. Weights are provided by the UBOS and change over time. A robustness check will be presented later on in order to check whether weights are the driving force behind empirical findings. To study child labour and schooling at the extensive margin, linear probability models are applied with binary dependent variables as extensions to the main model. $\beta_2 < 0$ is expected as far as children‘s market and farm work is concerned.

The number of household members (*HH_no*) in each wave is used as a control variable, because it could influence estimates and is not absorbed by FE. As described in the theoretical model, total household labour supply may affect child labour decisions. Higher household size means higher household labour supply. More household members can also imply more children and elderly people that other family members take care of (Björkman-Nyqvist 2013). This would translate into higher domestic labour demand. In the UNPS data the number of household members varies across waves for several households. It is not constant if a household member migrates or starts his or her own family. In the context of Uganda further variation in household size is caused by child fostering which is a common practice in sub-Saharan Africa[19].

Child time allocation is one decision-making process in which labour and schooling are chosen simultaneously. Since economic shocks affect both components, school attendance is not an appropriate control variable here. Beegle, Dehejia and Gatti (2006) use additional controls such as mother‘s and father‘s education level. They are assumed not to considerably vary over time and are thus supposed to be captured by household FE in this study. Increasing age is absorbed by community-time dummies.

For this identification strategy the shock needs to be transitory and exogenous to child labour decisions. Besides it should come with sufficient magnitude such that child time allocation and income are affected (Beegle, Dehejia and Gatti 2006).

This study focuses on droughts. Their self-reported incidence is used as the main explanatory variable. Droughts represent unpredictable weather shocks. As droughts are shocks on production (Cogneau and Jedwab 2012), they correspond to the shock parameter in the conceptual framework. Droughts are likely to hit farm households as an income shock and influence household members‘ marginal product of farm work. In Uganda where most households rely on farm-related income and labour, droughts are highly relevant. Informal risk-sharing mechanisms can hardly fully mitigate aggregate shocks like droughts (Cogneau and Jedwab 2012). Adjustment in household labour supply is hence more likely to be used as a coping strategy here. This is in contrast to idiosyncratic shocks that may be overcome by informal insurance arrangements. Additionally, droughts come with sufficient variation to draw reliable conclusions from the estimation. Endogeneity issues are discussed in chapter 4.6.

Even though this model cannot fully disentangle the effect of shocks on child labour into its components, it is able to examine the total effect of shocks on child labour. So the results allow for conclusions on which argument (I or II) is dominant.

[19] Child fostering means that "a non-orphaned child is sent to live temporarily with relatives" (Serra 2009: 157). Serra (2009) also develops a theoretical framework for child fostering.

4.4 Results

Various shock measurements - drought, floods and pest infestation - are used first to identify the most relevant event. Table 11 summarizes estimates for basic FE regressions (without additional controls). The number of hours children spent on agriculture is used as the dependent variable, since this type of work is likely to be affected by agricultural shocks. The results indicate that droughts have a statistically significant impact on children‘s on-farm work, while floods and pest infestations do not. Yet the variation in the dummy variable for floods and pest infestation is rather low (table 18). High standard errors point to limited precision of these estimates (Kohler and Kreuter 2012: 204). Consequently, the following estimations focus on droughts.

Table 11. Basic estimation for different shocks

	(1)	(2)	(3)
	Agriculture	**Agriculture**	**Agriculture**
drought	-0.734**		
	(0.345)		
floods		0.205	
		(0.830)	
pest			0.258
			(1.088)
Observations	7,856	7,856	7,856
$\mathbf{R^2}$	0.483	0.482	0.482

Sample includes children aged 6 to 13 who were interviewed at least twice.
Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Observations are weighted based on the sampling design. Standard errors are shown in parentheses. Standard errors are clustered at the household level. Fixed effects at the household level are used in all models.
*Asterisks indicate p-values according to: *** p<0.01, ** p<0.05, * p<0.1.*

Table 12 provides more details on the effect of droughts on child labour. For market and non-market work a basic FE model and the main specification (equation 12) are applied, respectively. In neither model droughts have a statistically significant effect on children‘s market or non-market work in total in a household, other things being equal. These dependent variables consist of different activities.

Table 12. Estimation results for market and non-market work in total

	(1)	(2)	(3)	(4)
Dependent Variable	**Market work**	**Market work**	**Non-market work**	**Non-market work**
Controls	No	Yes	No	Yes
Community-wave dummies	No	Yes	No	Yes
drought	-0.519	-0.370	-0.864	-0.679
	(0.521)	(0.508)	(0.562)	(0.619)
HH_no		-0.064		-0.415
		(0.236)		(0.354)
season		-0.036		-2.701
		(1.312)		(1.873)
2.wave		-6.492		10.168
		(6.302)		(7.380)
3.wave		-5.682***		3.890**
		(1.605)		(1.943)
Observations	7,856	7,856	7,856	7,856
R^2	0.460	0.545	0.482	0.563

*Sample includes children aged 6 to 13 who were interviewed at least twice. Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Observations are weighted based on the sampling design. Standard errors are shown in parentheses. Standard errors are clustered at the household level. Fixed effects at the household level are used in all models. Asterisks indicate p-values according to: *** p<0.01, ** p<0.05, * p<0.1.*

Since the shock may not equally affect different activities, it is crucial to split child labour up in its components. Table 13 shows estimation results for non-market labour activities. Droughts have a statistically significant impact on agricultural work. As the sign of the coefficient estimate is negative, the experience of a drought, i.e. if the shock variable moves from 0 to 1, is associated with a decrease in children‘s on-farm work by 0.73 to 0.85 hours in a household, other things being equal. Compared to the mean (table 8) the latter estimate implies an average decrease by 33 %. In both models - with and without controls and community-wave dummies - coefficient estimates on drought are statistically significant at the 5 % level indicating quite strong empirical evidence. The results, thus, support argument II: child labour on the farm decreases as a response to shocks. While the empirical findings do not confirm the hypothesis for market work, they do confirm the hypothesis in terms of agricultural work. The effect is assumed to be caused by lower marginal product of farm work. The model controls for household size which could influence child labour decisions as well.

Farm work is directly related to the shock. As predicted by the theoretical model, the time children spend on this activity is adjusted. Variables are designed such that agricultural work is part of total hours spent on non-market labour activities. Yet no significant changes in the latter are found. Is the decline in on-farm work compensated by more hours worked in other non-market activities? The estimates do not indicate such a shift. For time spent on collecting firewood and fetching water the estimated coefficients on drought show no statistical significance at conventional levels, other things being equal.

Table 13. Estimation results for non-market labour activities

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	**Collecting firewood**	**Collecting firewood**	**Fetching water**	**Fetching water**	**Agricul-ture**	**Agricul-ture**
Controls	No	Yes	No	Yes	No	Yes
Community-wave dummies	No	Yes	No	Yes	No	Yes
drought	0.102	0.151	-0.274	-0.036	-0.734**	-0.850**
	(0.126)	(0.134)	(0.316)	(0.317)	(0.345)	(0.409)
HH_no		-0.101		-0.078		-0.268
		(0.105)		(0.142)		(0.215)
season		-0.490		0.205		-2.352**
		(0.511)		(0.842)		(1.149)
2.wave		2.984		6.544		0.534
		(2.178)		(4.966)		(4.098)
3.wave		2.408***		5.641***		-4.204**
		(0.801)		(1.065)		(2.096)
Observations	7,856	7,856	7,856	7,856	7,856	7,856
R^2	0.452	0.531	0.487	0.565	0.483	0.568

*Sample includes children aged 6 to 13 who were interviewed at least twice. Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Observations are weighted based on the sampling design. Standard errors are shown in parentheses. Standard errors are clustered at the household level. Fixed effects at the household level are used in all models. Asterisks indicate p-values according to: *** p<0.01, ** p<0.05, * p<0.1.*

Unfortunately, non-market work cannot be completely analysed. It additionally includes construction work, processing food, conducting major repairs, handicraft and fishing. However, their variation in the clusters is not sufficient to estimate the models. This is not surprising, given the descriptive data shown in table 8 and table 4.[20]

As an extension to the results above, linear probability models are applied as well. Table 14 shows that children‘s non-market work indeed changes at the extensive margin. Other things being equal, the experience of a drought on average raises the probability that a child in a household is engaged in non-market labour activities by 5.1 percentage points. Children‘s mean probability to fetch water increases by 6.6 percentage points. Both effects are statistically significant at the 5 % level. No statistically significant linear dependence of on-farm work participation on drought is detected. The same holds for market work, collecting firewood and school attendance. The increase in non-market work participation seems to result from the impact of the economic shock on children‘s probability to help with fetching water in a household.

Table 14. Estimation results for linear probability models

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable (binary)	**Schooling**	**Market work**	**Non-market work**	**Collecting firewood**	**Fetching water**	**Agriculture**
drought	0.014	-0.011	0.051**	0.016	0.066**	-0.039
	(0.016)	(0.026)	(0.023)	(0.029)	(0.026)	(0.029)
Observations	7,856	7,856	7,856	7,856	7,856	7,856
R^2	0.475	0.577	0.525	0.559	0.522	0.579

*Sample includes children aged 6 to 13 who were interviewed at least twice. Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Observations are weighted based on the sampling design. Controls include household size as well as wave and season dummies (not displayed). Standard errors are shown in parentheses. Standard errors are clustered at the household level. Fixed effects at the household level and community-time dummies are used in all models. Asterisks indicate p-values according to: *** p<0.01, ** p<0.05, * p<0.1.*

So the decrease in children‘s on-farm hours as a response to droughts does not directly translate into more work at home in terms of hours. But children are more likely to be engaged in non-market labour activities, namely in fetching water. Several explanations are possible here.

[20] Estimation is technically possible for repairs. The coefficient on drought is statistically insignificant.

First, children may substitute for adult labour in household chores if their parents now work outside the household to generate further income. Substitution patterns are suggested by the conceptual framework and by other authors (Edmonds and Pavcnik 2005, Maldonado and González-Vega 2008). The assumption is related to the income channel of economic shocks: To smooth consumption, household labour supply is adjusted to cope with temporary income loss (see table 6 for self-reported coping strategies). Results do not suggest that it is the children who work more or are more likely to be engaged in income generating market work (argument I). But adults may work more and so a child‘s probability to help with domestic chores in a household rises as a response to droughts. Since adult labour supply is not included in the empirical model, findings do not allow for an explicit conclusion here.

Second, droughts limit the availability of water. More efforts are required to provide the household with water, especially in rural areas where local wells may fall dry at low water in times of droughts. As such, droughts could cause an increase in (child) labour demand in this activity which seems quite reasonable given the nature of a drought. Empirical results suggest that children on average work less hours on the farm and are more likely to fetch water. From a microeconomic point of view, such a shift in labour supply is expected, because on the other hand the marginal product of a child‘s farm work decreases due to the drought. Higher work participation of children regarding fetching water, again, seems to support the logic of argument II: children reallocate their labour as a response to shocks according to their marginal product of labour in different activities. While droughts limit opportunities for on-farm work, spending time on fetching water is now more efficient.

However, the shift is not confirmed by the number of hours children spend on fetching water. This would be expected if children spent time on working only as simplified as in the numerical example. Yet this is, of course, not the case. Schooling and leisure are relevant as well. According to the results for schooling shown in table 14, droughts do not have a statistically significant effect on school attendance at the extensive margin if the other variables included in the model are fixed. Note that for school attendance variation in the dependent variable is low. Most children in the sample do go to school. In addition to that, primary schooling is free in Uganda. If droughts induce income shocks, withdrawing children from school in order to reduce expenditures and smooth consumption is therefore not an effective coping strategy.

The time children spend on school attendance, learning outside of school, leisure, or other activities such as taking care of younger siblings or the elderly is unknown. It is thus not appropriate to draw conclusions about adjusted leisure time based on significantly less hours spent on the family farm (Hazarika and Sarangi 2008). Consequently, the welfare argument of Cameron and Worswick (2003) cannot be applied either. Conclusions about leisure and welfare effects are likely to exceed what the estimations are able to explain, given the fact that the empirical analysis cannot completely examine children‘s reallocation of time.

The estimated coefficients describe how an economic shock affects child labour controlling for other factors like household size and time of the interview. Coefficients on control variables do not have a causal interpretation but are included to reduce potential omitted variable bias of the coefficient on drought (Stock and Watson 2012: 274). Yet estimated coefficients on some regressors suggest interesting patterns. The coefficient on season is significantly different from zero as far as on-farm child labour is concerned pointing to seasonal differences in agricultural work. Several estimates indicate different working patterns across waves. Based on the descriptive analysis, a positive sign of the coefficient on wave 3 for market work and farm work would have been expected but community-wave dummies may already absorb this effect.

The findings discussed above are directly related to the literature. De Janvry et al. (2006) also show that child labour significantly decreases as a response to droughts but they analyse market work at the extensive margin only. Their estimates suggest an average change of children‘s work participation of approximately -7.5 percentage points. In contrast, the estimates for the UNPS data do not indicate reduced market work of children. Yet less child labour is found with respect to the number of hours spent on the farm. Similar to De Janvry et al. no statistically significant effects are found for school attendance. In addition to that, the empirical results of this paper broadly correspond to the findings of Soares, Kruger and Berthelon (2012) regarding child labour. But again, comparing their empirical findings with the results of this study is difficult because of different variable definitions and empirical specifications.

By contrast, Beegle, Dehejia and Gatti (2006) support argument I. They find that the mean hours children work significantly increase as a response to a shock. The authors also detect statistically significant increases in children‘s time spent on domestic chores. Using panel data for Uganda this analysis finds more child labour in non-market labour activities at the extensive margin only. The results of Dillon (2013) are not confirmed by this study either. He finds significantly higher participation in farm work as a response to crop loss.

In summary, the estimates provide empirical evidence for complex and shock-specific adjustments in a child‘s working pattern when households are exposed to shocks. Children‘s market work is not significantly affected. But children are found to spend significantly less time on the farm if their households experience a drought, other things being equal. This finding supports argument II. The marginal product of farm work seems to be reduced by a drought so children spend less time working on the farm. In addition to that, children are more likely to help with household chores, namely fetching water, when living in families that are exposed to droughts. Children may substitute for reallocated adult labour in domestic chores if parents work more outside home as a response to income shocks. But it seems also reasonable to apply the assumption of child labour responses according to adjusted marginal product of labour (argument II) here as well - but in the opposite direction.

4.5 Robustness checks

The main empirical analysis shows that child labour on the farm statistically significantly decreases when households experience a drought. The results confirm the hypothesis for farm work, but not for market work (argument II). As shown in the following, findings are very robust to various specifications.

Table 15 presents four different robustness checks. The descriptive analysis pointed to several difficulties regarding the third survey round. The main specification uses wave dummies. Nevertheless sampling concerns remain so that a robustness check (I) is conducted in order to check whether this survey round drives the results. The coefficients of interest remain very robust to the adjusted sample in terms of sign and magnitude. On-farm child labour still decreases with statistical significance. In the main specification the coefficient on drought is significant at the 5 % level. However, by focusing on the first two waves only the null hypothesis that the effect of a drought on farm work is zero can only be rejected at the 10 % level.

The definition of a child‘s age may be crucial for empirical results as well. This is examined in the second robustness check (II). The main specification includes children aged 6 to 13 in the sample because it covers the period of compulsory schooling. Two concerns arise: first, many pupils in Uganda are over-aged as discussed above. Looking only at children aged 6-13 neglects pupils with higher productivity who may rather be sent to work as a response to economic shocks than younger children. Second, several studies on child labour such as Soares, Kruger and Berthelon (2012) use 14 as the upper bound. In order to be able to compare the results to other studies an extended sample including 14-year old teenagers seems reasonable. For market work, non-market work as well as agriculture the coefficients on drought remain robust in sign, significance and magnitude. The shock is not associated with a statistically significant change in the time a child in a household spends on market or domestic activities in total. However, on-farm work significantly decreases.

The main specification uses community-wave dummies. Following Beegle, Dehejia and Gatti (2006), the model is also estimated without these dummies as a robustness check (III). There are only slight changes in significance level and magnitude. On average, when hit by a drought children‘s farm work now decreases by 0.63 hours, other things being equal. The coefficient is statistically significant at the 10 % level.

Table 15. Robustness Checks I

	I			II			III			IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable	**Market work**	**Non-market work**	**Agriculture**	**Market work**	**Non-market work**	**Agriculture**	**Market work**	**Non-market work**	**Agriculture**	**Market work**	**Non-market work**	**Agriculture**
Waves	1-2	1-2	1-2	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3
Child age	6-13	6-13	6-13	6-14	6-14	6-14	6-13	6-13	6-13	6-13	6-13	6-13
Community-wave dummies	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
drought	-0.21	-0.59	-0.83*	-0.36	-0.83	-0.92**	-0.28	-0.54	-0.63*	-0.34	-1.04*	-1.06***
	(0.60)	(0.71)	(0.48)	(0.50)	(0.61)	(0.39)	(0.55)	(0.59)	(0.38)	(0.47)	(0.58)	(0.40)
HH_no	-0.15	-0.62	-0.36	-0.18	-0.43	-0.27	-0.16	-0.24	-0.21	-0.02	-0.40	-0.33
	(0.27)	(0.39)	(0.24)	(0.23)	(0.34)	(0.21)	(0.28)	(0.41)	(0.25)	(0.23)	(0.35)	(0.22)
Observations	7,121	7,121	7,121	9,068	9,068	9,068	7,856	7,856	7,856	7,856	7,856	7,856
R^2	0.50	0.55	0.53	0.54	0.53	0.54	0.47	0.49	0.49	0.50	0.53	0.52

*Number of observations changes due to different sample definitions as stated in the first rows. Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Controls include household size as well as wave and season dummies (not displayed). Standard errors are shown in parentheses. Standard errors are clustered at the household level. Fixed effects at the household level are used in all models. Asterisks indicate p-values according to: *** p<0.01, ** p<0.05, * p<0.1.*

Sampling weights are included to reflect the complex sampling design of the data. Robustness check (IV) shows estimation results without weights. Argument II is supported by this specification as well. The impact of a drought on child farm labour is now slightly higher in magnitude and significant at the 1 % level. The hypothesis that the shock affects children‘s total non-market work cannot be rejected at the 10 % level. If this specification is used, the decrease in children‘s on-farm work translates into a reduction in the total number of hours they work in non-market labour activities. The point estimates of drought are very similar for non-market and on-farm hours indicating that less work on non-market labour activities is caused by less agricultural work. The main specification is more conservative. Neglecting complex sampling design implies simple random sampling. It results in biased coefficients and wrong confidence intervals if the sampling design is more complex (Kohler and Kreuter 2012: 75).

The same robustness checks are applied to linear probability models (table 16). Empirical findings of increased participation in fetching water and non-market labour activities in total as a response to droughts are robust to most adjustments. Excluding wave 3, widening children‘s age range or removing weights do not change coefficient estimates considerably in terms of sign, significance and magnitude. Yet statistical significance disappears for non-market labour activities without community-wave dummies (VII). Regarding fetching water (column (8) in table 16) the estimated coefficient on drought indicates a slightly smaller effect on child labour in this activity (4 percentage points) and a lower significance level compared to the main specification.

By using the extended sample (VI) and excluding weights (VIII) a statistically significant reduction is found in a child‘s farm work participation in a household as a response to droughts, other things being equal. The probability that children are engaged in agricultural work decreases by 5 to 4 percentage points which, again, supports argument II. This result confirms the finding of lower hours spent on the farm at the extensive margin, but it is only significant at the 10 % level. Despite this significant reduction in farm work, children‘s participation in non-market labour activities is still positively affected by the shock. The coefficient estimates on drought in column (4) and (10) are similar to the respective coefficients in the main specification in terms of sign, significance level and magnitude. In comparison to this result, the main model does not detect statistically significant changes in children‘s farm work participation.

Table 16. Robustness Checks II

	V			VI			VII			VIII		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable (binary)	**Non-market work**	**Fetching water**	**Agricul-ture**	**Non-market work**	**Fetching water**	**Agricul-ture**	**Non-market work**	**Fetching water**	**Agricul-ture**	**Non-market work**	**Fetching water**	**Agricul-ture**
Waves	1-2	1-2	1-2	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3
Child age	6-13	6-13	6-13	6-14	6-14	6-14	6-13	6-13	6-13	6-13	6-13	6-13
Community-wave dummies	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
drought	0.06**	0.07**	-0.03	0.05**	0.06***	-0.05*	0.02	0.04*	-0.02	0.04**	0.04*	-0.04*
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Observations	7,121	7,121	7,121	9,068	9,068	9,068	7,856	7,856	7,856	7,856	7,856	7,856
$\mathbf{R^2}$	0.52	0.52	0.55	0.50	0.50	0.56	0.48	0.47	0.52	0.51	0.50	0.57

*Number of observations changes due to different sample definitions as stated in the first rows. Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Controls include household size as well as wave and season dummies (not displayed). Standard errors are shown in parentheses. Standard errors are clustered at the household level. Fixed effects at the household level are used in all models. Asterisks indicate p-values according to: *** p<0.01, ** p<0.05, * p<0.1.*

4.6 Discussion and limitations

In order to confirm that the empirical identification strategy is credible, endogeneity issues must be eliminated. Applying household FE largely copes with the empirical challenge to disentangle the link between a household‘s complex (time-invariant) economic conditions and its decisions on child labour. Climatic shocks such as droughts can be seen as more exogenous to households than shocks related to illness or unemployment (De Janvry et al. 2006). Shocks are measured by their incidence and not by loss of income or harvest, because the latter are more likely to already incorporate applied coping strategies and suffer from measurement error (Alvi and Dendir 2011).

But it is not possible to rule out any source of endogeneity: Household‘s expectations of future income are relevant, particularly for idiosyncratic income shocks to peasant households. If they expect limited rainfall, they will focus on drought-resistant crops (Kochar 1999). The decision is based on available information and may not be captured by FE. It challenges the assumption that self-reported incidence of drought represents an exogenous source of variation. Shocks are self-reported by households and not based on official weather data. Besides, reverse causation cannot totally be ruled out. If households whose children work are more likely to be hit by droughts the explanatory power of its coefficient is limited (Beegle, Dehejia and Gatti 2006).

Table 17. T-tests for attrition

	Mean Singletons	**Mean Panel**	**Diff.**	**p-value**
Market work	5.46	4.11	1.35	0.00
Non-market work	5.90	6.49	-0.59	0.11
Agriculture	1.60	2.00	-0.40	0.09
Drought	0.27	0.35	-0.07	0.00

Data source: UNPS.

Sample consists of all children aged 6-13 including those who have missing information on control variables. Observations are weighted based on the sampling design.

Another concern is non-random attrition. If children or families are not re-interviewed for any reason that is systematically related to droughts or child labour, coefficients will be probably biased (Beegle, Dehejia and Gatti 2006). This is the case, for instance, if children move for work and exit or enter the sample by doing so. With child fostering being a common practice in Uganda, non-random attrition is likely to be a concern. Attrition of households does not cause bias if attrition is related to time invariant household characteristics only, as they are ruled out by household FE (De Janvry et al. 2006). T-tests of means are applied to test whether children that were interviewed in at least two waves work on average the same hours as children recorded only once. Table 17 indicates that the sub-samples significantly differ in hours spent on market work. The value is higher among singletons. Significant differences are also found for the incidence of a drought. According to the t-tests, non-random attrition must be acknowledged as a limitation to the analysis.

Several individuals are continuously recorded, but some data on them is not. As long as irregularities follow a random pattern, estimates are unaffected. Nevertheless their precision could be increased by using a larger sample, since standard errors decrease in sample size (Stock and Watson 2012: 519). Table 25 in the appendix points to a considerable number of children whose age is unknown. More than 50 % of 2515 observations with missing age data are sons, daughters, grand children, nephew or niece of the household head. So better data quality could allow for more precise estimates and hypothesis tests. Such issues are common for LIC data.

Measurement error is another issue that arises in child labour studies. Interviewees may have a different concept of "work" which makes it difficult for them to assess working hours according to standard definitions used in the surveys (Dillon et al. 2012). Measurement errors are particularly likely for children who work on the family farm or help in the household business. As discussed above, this is also the reason why the structure of the questionnaire makes it difficult to isolate children‘s on farm work. Measurement errors in the dependent variable usually do not bias the estimated coefficient but increase its variance (Stock and Watson 2012: 363). Additionally, answers on schooling and children‘s work may suffer from social desirability bias (Edmonds and Shrestha 2014). However, household‘s attitudes towards education and child labour are absorbed by household FE (Beegle, Dehejia and Gatti 2006).

The discussion has pointed to several issues challenging the internal validity of this study. Even though the empirical model can deal with some sources of endogeneity, other forms of endogeneity cannot be ruled out completely. The relationship between droughts and child labour is not supposed to be interpreted as a precise causal effect.

5 Conclusion

This paper studies the effect of economic shocks on child labour by using household survey data from Uganda.

The literature review identifies two channels of how economic shocks affect a household‘s child labour decision in LIC. First, child labour may increase as a coping mechanism to smooth consumption when exposed to an income shock. This is what most studies suggest. Second, child labour may decrease if children‘s marginal product of labour in certain activities is adversely affected by the shock. The conceptual framework of Dillon (2013) makes it possible to formally model the latter argument.

The empirical analysis in this paper supports the second reasoning. Findings suggest that a drought significantly decreases the mean time children spend on the farm by 0.85 hours a week, other things being equal. Linear probability models are presented as extensions to this result. They do not support the finding of less agricultural work at the extensive margin. Yet droughts are associated with a significantly higher work participation of children in fetching water and non-market labour activities in total. Estimates suggest that on average children‘s probability to fetch water rises by 6.6 percentage points, other things being equal. Their probability to be engaged in non-market labour activities increases by 5.1 percentage points. No statistically significant effects on children‘s market work are found in any empirical model applied in this study. In addition to that, estimates do not suggest school attendance to be statistically significantly affected by droughts. The estimated coefficients have proved to be very robust to several specifications and sample adjustments.

The empirical result that children in households that are hit by a drought work less on the farm seems to be caused by a child‘s lower marginal product of labour in this activity. Droughts limit opportunities to work on the household farm. Children‘s work on agriculture becomes therefore less productive if households experience a drought.

On the other hand, children are found to be more likely to spend time on fetching water. This result can be understood by applying either argument. First, with droughts inducing income shocks for peasant households, parents may take on more work outside the household. Children’s work then substitutes adult labour in domestic chores. Second, droughts can directly increase labour demand in fetching water. By reducing on-farm work and being more likely to fetch water, children seem to adjust labour supply according to their marginal product of labour in different activities. Given the fact that this empirical analysis does not incorporate adult labour, it does not reveal which of the two channels drives the results in this case. Nevertheless, the discussion of the microeconomic model shows that the conceptual framework applied in this study can be useful to analyse intra-household labour substitution theoretically.

Panel data allow for adequate econometric tools to cope with unobserved, time invariant heterogeneity. However, some endogeneity issues remain, which have to be acknowledged as limitations to the analysis. In particular non-random attrition and reverse causality cannot be ruled out. Self-reported shocks may not represent an exogenous source of variation but could be directly related to child labour decisions. The discussion of different threats to internal validity shows that the estimates should not be interpreted as causal effects.

The findings of this paper point to further research questions that could be addressed in future studies. First, additional investigations are necessary to fully understand substitution patterns between adult labour and child labour. Second, more attention should be paid to child labour in activities that are directly affected by the shock. For instance, making major repairs and agricultural work may be relevant in case of floods. Children‘s time spent on domestic chores can be particularly interesting if a female adult in the household falls ill. Detailed survey data is necessary to analyse shock-specific adjustments in child labour. Datasets that are made available by the LSMS programme provide rich data sources for child labour studies.

This study finds complex patterns of children‘s work when households in LIC experience economic shocks. Both the theoretical framework and the empirical approach have turned out to be fruitful in order to study the relationship between economic shocks and child labour in more detail in this setting.

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7 Appendix

Appendix A: Numerical example

Based on Dillon‘s conceptual framework, a numerical example will be described in the following to illustrate the effect of a production shock on child labour in more detail. To keep it simple, the two-period utility maximization problem is reduced to a one-period profit maximization problem. This is a reasonable approach given the fact that in the complete model utility depends on consumption only and income is generated by market and household production using adult and child labour as input factors. The output price for the good generated by home production can be seen as the numeraire price. Apart from that, wages differ for children and adults but not across different occupations, respectively. Adults do not have the opportunity to work for wages in the labour market. As shown in table 21, labour markets are imperfect in Uganda. Most adults work on the household farm or as own-account workers. Schooling and leisure are neglected. Hence, children cannot increase total labour supply here by reducing time spent on schooling or leisure. The numerical example focuses on how households reallocate a given amount of labour supply among market and home production.

Cobb-Douglas production technologies are used to describe household‘s market and home production. The share of output earned by adult labour is assumed to be higher than the share of output earned by child labour in both technologies, but the difference is greater for market production. Production functions are defined as follows:

$$q = \left(T_A^F\right)^{\frac{3}{4}} \left(T_C^F\right)^{\frac{1}{4}} \tag{13}$$

$$h = \left(T_A^H\right)^{\frac{2}{3}} \left(T_C^H\right)^{\frac{1}{3}}. \tag{14}$$

Combining the information above the Lagrangian function is

$$\begin{aligned} \max_{T_C^F, T_C^H, T_A^F, T_A^H} \hat{\mathscr{L}} = & p\delta \cdot q\left(T_A^F, T_C^F\right) - w_A T_A^F - w_C T_C^F + h(T_A^H, T_C^H) - w_A T_A^H - w_C T_C^H \\ & + \lambda_A (T_A - T_A^F - T_A^H) + \lambda_C (T_C - T_C^F - T_C^H). \end{aligned} \tag{15}$$

The first order conditions are shown below:

$$\frac{\partial \hat{\mathscr{L}}}{\partial T_A^F} \overset{!}{=} 0 \quad \longleftrightarrow \quad p\delta \cdot \frac{\partial q}{\partial T_A^F} = w_A + \lambda_A \tag{16}$$

$$\frac{\partial \hat{\mathscr{L}}}{\partial T_A^H} \overset{!}{=} 0 \quad \longleftrightarrow \quad \frac{\partial h}{\partial T_A^H} = w_A + \lambda_A \tag{17}$$

$$\frac{\partial \hat{\mathscr{L}}}{\partial T_C^F} \overset{!}{=} 0 \quad \longleftrightarrow \quad p\delta \cdot \frac{\partial q}{\partial T_C^F} = w_C + \lambda_C \tag{18}$$

$$\frac{\partial \hat{\mathscr{L}}}{\partial T_C^H} \overset{!}{=} 0 \quad \longleftrightarrow \quad \frac{\partial h}{\partial T_C^H} = w_C + \lambda_C \tag{19}$$

$$\frac{\partial \hat{\mathscr{L}}}{\partial \lambda_A} \overset{!}{=} 0 \quad \longleftrightarrow \quad T_A = T_A^F + T_A^H \tag{20}$$

$$\frac{\partial \hat{\mathscr{L}}}{\partial \lambda_C} \overset{!}{=} 0 \quad \longleftrightarrow \quad T_C = T_C^F + T_C^H. \tag{21}$$

Putting together equations (16) and (17) as well as equations (18) and (19) yields

$$p\delta \cdot \frac{\partial q}{\partial T_A^F} = \frac{\partial h}{\partial T_A^H} \tag{22}$$

$$p\delta \cdot \frac{\partial q}{\partial T_C^F} = \frac{\partial h}{\partial T_C^H}. \tag{23}$$

Dividing equation (22) by equation (23) gives

$$\frac{\frac{\partial q}{\partial T_A^F}}{\frac{\partial q}{\partial T_C^F}} = \frac{\frac{\partial h}{\partial T_A^H}}{\frac{\partial h}{\partial T_C^H}}. \tag{24}$$

Deriving the marginal products based on equations (13) and (14) and plugging it in the equation above yields

$$\frac{\frac{3}{4} \cdot \left(T_A^F\right)^{-\frac{1}{4}} \cdot \left(T_C^F\right)^{\frac{1}{4}}}{\frac{1}{4} \cdot \left(T_A^F\right)^{\frac{3}{4}} \cdot \left(T_C^F\right)^{-\frac{3}{4}}} = \frac{\frac{2}{3} \cdot \left(T_A^H\right)^{-\frac{1}{3}} \cdot \left(T_C^H\right)^{\frac{1}{3}}}{\frac{1}{3} \cdot \left(T_A^H\right)^{\frac{2}{3}} \cdot \left(T_C^H\right)^{-\frac{2}{3}}} \tag{25}$$

which can be rewritten to

$$\frac{2}{3} \cdot \frac{T_A^F}{T_C^F} = \frac{T_A^H}{T_C^H}. \tag{26}$$

The equation above will be used later to combine child and adult labour in equilibrium. Looking at adult labour first, the partial derivatives of market and home production can be plugged in equation (22) such that

$$\frac{9}{8} \cdot p\delta \cdot \left(\frac{T_C^F}{T_A^F}\right)^{\frac{1}{4}} = \left(\frac{T_C^H}{T_A^H}\right)^{\frac{1}{3}}. \tag{27}$$

Let the non-sleeping time of adults and children per day be 16 hours ($T_A = T_C = 16$) as suggested by Strulik (2013). Equations (20) and (21) as well as the above can be put together to

$$T_A^F = \left(\frac{9}{8} \cdot p\delta\right)^4 \cdot T_C^F \cdot \left(\frac{16 - T_A^F}{16 - T_C^F}\right)^{\frac{4}{3}}. \tag{28}$$

Going back to the first order conditions related to child labour and plugging in the marginal product of children‘s work in market and home production in equation (23) yields

$$\frac{3}{4} \cdot p\delta \cdot \left(\frac{T_A^F}{T_C^F}\right)^{\frac{3}{4}} = \left(\frac{T_A^H}{T_C^H}\right)^{\frac{2}{3}}. \tag{29}$$

By using equation (26) labour inputs to home production can be eliminated:

$$\frac{3}{4} \cdot p\delta \cdot \left(\frac{T_A^F}{T_C^F}\right)^{\frac{3}{4}} = \left(\frac{2}{3} \cdot \frac{T_A^F}{T_C^F}\right)^{\frac{2}{3}}. \tag{30}$$

Rewriting the above to

$$T_C^F = \left(\frac{3}{4} \cdot p\delta\right)^{12} \left(\frac{3}{2}\right)^8 \cdot T_A^F \tag{31}$$

and plugging it in equation (28) yields

$$T_A^F = \left(\frac{9}{8} \cdot p\delta\right)^4 \left(\frac{3}{4} \cdot p\delta\right)^{12} \left(\frac{3}{2}\right)^8 \cdot T_A^F \cdot \left(\frac{16 - T_A^F}{16 - \left(\frac{3}{4}p\delta\right)^{12}\left(\frac{3}{2}\right)^8 T_A^F}\right)^{\frac{4}{3}}. \tag{32}$$

Solving for T_A^F finally gives

$$T_A^F = \frac{16}{(p\delta)^{12}\left(\frac{3}{2}\right)^6\left(\frac{3}{4}\right)^9} \cdot \frac{(p\delta)^{12}\left(\frac{3}{2}\right)^6\left(\frac{3}{4}\right)^9\left(\frac{9}{8}\right)^3 - 1}{\left(\frac{9}{8}\right)^3 - \left(\frac{3}{2}\right)^2\left(\frac{3}{4}\right)^3}. \tag{33}$$

Without production shock ($\delta = 1$) and a price $p = 1.01$ the solutions of the optimization problem are as follows:

$$\begin{aligned} T_A^F &\approx 13 \\ T_A^H &\approx 3 \\ T_C^F &\approx 11.9 \\ T_C^H &\approx 4.1. \end{aligned}$$

A production shock that reduces output by 2 % already induces considerable changes in the distribution of household labour supply. For $p = 1.01 = const.$ and $\delta = 0.98$ adult and child reallocate their time as follows:

$$\begin{aligned} T_A^F &\approx 3.4 \\ T_A^H &\approx 12.6 \\ T_C^F &\approx 2.5 \\ T_C^H &\approx 13.5. \end{aligned}$$

Therefore, both adult and child spend less time on market production and more time on home production. The result is caused by the reduced marginal product of labour in market production.

Appendix B: Tables and figures

Table 18. Shocks by wave

	Wave of Panel							
	1		2		3		Total	
	No.	Col %	No.	Col %	No.	Col %	No.	Col %
Experienced drought								
No	1442	47.7	3071	72.8	422	68.6	4934	62.8
Yes	1580	52.3	1149	27.2	193	31.4	2922	37.2
Experienced floods								
No	2962	98.0	4057	96.1	590	95.9	7608	96.8
Yes	60	2.0	163	3.9	25	4.1	248	3.2
Experienced pest								
No	2841	94.0	4136	98.0	590	95.8	7567	96.3
Yes	180	6.0	83	2.0	26	4.2	289	3.7

Data source: UNPS. Shocks experienced by households during the last 12 months, self-reported.
Baseline sample includes children aged 6-13 who were interviewed at least twice. Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Observations are weighted based on the sampling design.

Table 19. Land holdings by consumption expenditures (quantiles)

	5 quantiles of HH consumption expenditure					
5 quantiles of land holdings	1	2	3	4	5	Total
	Col %	Col %	Col %	Col %	Col %	Col %
1	10.5	11.6	15.3	21.2	24.3	15.5
2	44.3	34.1	23.1	20.0	8.8	28.7
3	18.2	20.9	16.9	12.2	6.7	16.0
4	18.3	23.2	26.8	24.7	20.1	22.6
5	8.7	10.1	17.9	22.0	40.1	17.2
Total	100.0	100.0	100.0	100.0	100.0	100.0

Data source: UNPS. Household's value of land holdings and monthly consumption expenditure (adjusted), self-reported.
Data on consumption is unknown for 7 observations of the baseline sample, data on land is unknown for 47 observations.
Baseline sample includes children aged 6-13 who were interviewed at least twice. Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Observations are weighted based on the sampling design.

Table 20. Non-market work by gender (unconditional)

	Mean hours worked		
	Female	**Male**	**Total**
Collecting firewood	1.39	0.92	1.15
Fetching water	3.97	3.32	3.64
Agriculture	2.30	2.88	2.59
Construction	0.01	0.02	0.02
Repairs	0.00	0.01	0.00
Processing food	0.09	0.02	0.05
Handicraft	0.02	0.01	0.02
Fishing	0.02	0.08	0.05

Data source: UNPS. Hours worked in non-market activities in the last 7 days.
Baseline sample includes children aged 6-13 who were interviewed at least twice.
Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Observations are weighted based on the sampling design.

Table 21. Employment status of adults

	Urban/Rural Identifier			
Employment status in main job	**Rural**	**Urban**	**Total**	**N**
	Col %	Col %	Col %	
Working for someone else for pay	10.0	30.9	12.3	1,379
Working for an employer	0.2	1.0	0.3	37
Own-account worker	11.2	28.3	13.0	1,528
Helping w/o pay in a household business	1.8	7.3	2.4	280
Apprentice	0.2	0.7	0.2	35
Working on household farm/with household livestock	76.6	31.7	71.8	7,755

Data source: UNPS. Data on main employment status of household members aged 14 and above. Data is unknown for 5209 observations. Sample includes only households that belong to the baseline sample.
Baseline sample includes children aged 6-13 who were interviewed at least twice. Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Observations are weighted based on the sampling design.

Table 22. Market and non-market work (unconditional)

	Mean hours worked	
	Market work	**Nonmarket work**
Gender		
Female	3.60	7.81
Male	4.63	7.25
Total	4.12	7.53
Urban/Rural Identifier		
Rural	4.39	8.00
Urban	1.69	3.33
Total	4.12	7.53
School attendance		
No	4.47	4.31
Yes	4.07	7.99
Total	4.12	7.53
Highest level of father's education completed		
No formal education	6.74	7.97
Less than Primary	3.92	7.76
Completed Primary	3.84	7.44
Completed O-Level	3.01	5.84
Completed A-Level	3.69	6.83
Completed University	1.42	3.65
Other (Specify)	5.67	11.59
Total	4.03	7.43
5 quantiles of land holdings		
1	3.86	7.22
2	4.50	8.24
3	4.17	7.69
4	4.03	7.72
5	3.81	6.22
Total	4.12	7.53

Data source: UNPS. Hours worked in market and nonmarket labour activities in the last 7 days.
Data on father's education is unknown for 955 observations of the baseline sample, so total hours differ in this part.
Baseline sample includes children aged 6-13 who were interviewed at least twice. Only children living in communities with at least 5 observations per wave are considered due to estimation requirements. Observations are weighted based on the sampling design.

Table 23. Variable labels

Variable name	Variable label
age	Age in completed years
sex	Gender, =1 if male
schooling	School attendance
hours_job	Hours worked in main and second job in the last 7 days
hours_nonmarket	Hours spent on non-market labour activities in the last 7 days
fetch_wood	Hours spent collecting firewood for the household in the last 7 days
fetch_water	Hours spent fetching water for the household in the last 7 days
construction	Hours spent constructing your dwelling etc. in the last 7 days
repairs	Hours spent making major repairs in the last 7 days
process_food	Hours spent on food processing for the household in the last 7 days
handicraft	Hours spent making handicrafts for household use in the last 7 days
agriculture	Hours spent on agriculture in the last 7 days
fishing	Hours spent on hunting and fishing in the last 7 days
job_d	Participation in Market work in the last 7 days (dummy)
nonmarket_d	Participation in Non-market work in the last 7 days (dummy)
fetch_wood_d	Participation in Collecting firewood in the last 7 days (dummy)
fetch_water_d	Participation in Fetching water in the last 7 days (dummy)
construction_d	Participation in Construction in the last 7 days (dummy)
repairs_d	Participation in Repairs in the last 7 days (dummy)
process_food_d	Participation in Processing food in the last 7 days (dummy)
handicraft_d	Participation in Handicraft in the last 7 days (dummy)
agriculture_d	Participation in Agriculture in the last 7 days (dummy)
fishing_d	Participation in Fishing in the last 7 days (dummy)
HH_no	Number of household members
urban	Urban/Rural Identifier
cons (ln)	Log of monthly HH consumption expenditure
land (ln)	Log of household land holdings (estimated value in Shs)
drought	Experienced drought during past 12 months
floods	Experienced floods during past 12 months
pest	Experienced pest during past 12 months
season	Interviewed during rainy season

Data source: UNPS.

Table 24. Household attrition by wave

Waves per household	Wave of Panel			
	1	**2**	**3**	**Total**
	Col %	Col %	Col %	Col %
1	9.5	2.4	30.1	14.2
2	13.4	13.1	12.2	12.9
3	77.1	84.6	57.7	73.0
Total	100.0	100.0	100.0	100.0

Data source: UNPS. Number of waves in which households were interviewed.
Sample refers to full sample before data cleaning.

Table 25. Relationship to household head of observations with missing age data

Relationship to household head	No.	Col %
Head	7	0.3
Spouse	169	6.7
Son/daughter	735	29.2
Grand child	456	18.1
Parent of head or spouse	61	2.4
Sister/Brother of head or spouse	250	9.9
Nephew/Niece	216	8.6
Other relatives	469	18.7
Servant	43	1.7
Non-relative	83	3.3
Other (specify)	26	1.0
Total	2515	100.0

Data source: UNPS. Observations with missing age data.

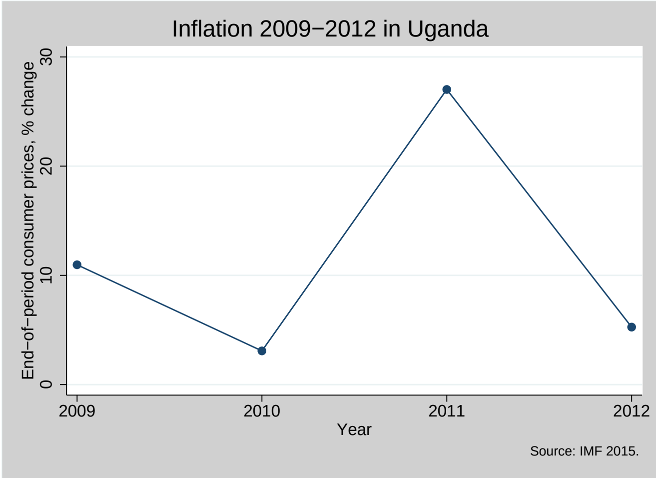

Figure 5. Inflation 2009-2012