The effect of drought on child labor in Ethiopia

Kebede Abrha Mengstu

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Department of Economics

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Abstract
This study explains the effect of drought on child labor using a panel data from 981 individuals. The data were collected and organized by the UK data service, Young Lives section in three survey rounds (2006-2013). Very few researchers have investigated the effect of drought on child labor, but its effect had been reported to be mixed depending on the dominance of the income and substitution effects of the child and adult labor. Drought is expected to influence the parent’s decision on the use of child’s time for work. Though drought appears to every household, at least in one district, exogenously the same, its perceived effect, however, can vary from one family to the other due to their personal and socioeconomic differences. Hence, the difference in the perception of drought brings a variation on the use of child labor across families and time periods. Child labor refers to the employment of children in any work at their childhood age. A family fixed Effect estimation was conducted to estimate the effect of drought on the log of average hours of work by a child. A drought was found to be associated positively and significantly with child labor. Children were observed to be working more hours when they or their family perceived the existence of a drought shock. This could be because families view the presence of drought is an indication of a drop in their consumption below the subsistence level. This perception might trigger them to take a child labor decision which is consistent with the child labor theory of the luxury axiom of (Basu and Van, 1998). The researcher recommends that governments, institutions and other stakeholders who are interested and committed to combat child labor should reach the drought-affected areas and families with support packages besides to promoting and implementation of drought-resilient live styles.

Key words: child labor, perception of drought, fixed effect panel data estimation
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Chapter 1: Introduction

1.1. Background of the study

A drought is one type of the most devastating climate shocks which severely affects the majority of the rain-dependent agricultural households. The world has experienced the warmest decade in history in the first decade of the 21 century (World Meteorological Organization, 2013). East Africa, where Ethiopia is located, was the most affected area by the natural disasters (like drought) in most of these warmest years. Close to 8 million people were in danger due to climate irregularities in Ethiopia in that decade (Hyder et.al.2016).

Nowadays a considerable attention has been given to the causes and consequences of climate shocks (for example, drought) on households. Many countries and agencies have been sending many types of aid to the drought-affected countries. An occurrence of drought is likely to affect the expenditure, consumption and investment opportunities of families especially in the least developed countries which they lack a drought-resilient economic system (Morton, 2007). Households might be forced to use child labor instead of sending them to school due to the family’s incapability to cope with the consequence of the drought. Hence, drought is expected to affect the use of child labor especially in the third world countries which their life is mainly rain-dependent subsistence agriculture and dysfunctional credit market.

There are many definitions of child labor from different perspectives while the main point they want to express is not different. The following definition describes the context of child labor adopted in this study.

Diallo et al., (2013) defined child labor as a work by which it can either deprive child’s schooling or requires them to assume the dual burden of education and work at their childhood age.

Child labor is a recently recognized issue in the global and local policy arena. Governments and nongovernment organizations have been showing their commitment to combat child labor and enforce laws accordingly. From the personal observations and some reports from child labor-related workshops and forums, it can be understood that the problem is not yet solved and the results gained so far seem too lagged compared to our expectations.
Most child labor theories and empirical researchers claim that the main cause of child labor is poverty. Accordingly, many governments, stakeholders, and institutions have been working to eradicate poverty, and remarkable results have been registered on the reduction of poverty globally. However, the performance recorded on child labor reduction is not remarkable compared to the performances recorded on poverty reduction and economic growth, especially in the sub-Saharan Africa countries. Ethiopia, for example, is one among the sub-Saharan countries, which has been registering a consistent double-digit economic growth for the past two decades, but has not registered a significant reduction in child labor simultaneously (UNICEF, 2012).

According to the recent statistical reports by (UNICEF, 2016) and (ILO, 2017), there are more than two hundred million children in the world who are engaged or victims in child labor activities. Concerning the prevalence of child labor, Africa leads by (19.6%) followed by Asia (7.4%). Agriculture takes the lion share regarding child labor concentration (71%).

Children are being exploited in both paid and unpaid work. The worst of this exploitation is happening in the least developed countries, Ethiopia is not an exception, today. Reports show that 55% of the Ethiopian children aged 12-14 were involved in child labor with a varying child labor percentage among regions from 7% in Addis Ababa to 42% in Tigray (Central Statistical Agency, 2012).

Not a small number of both local and multinational firms are employing children in their production and marketing activities. Most employers often choose a child over an adult employee because the later is relatively expensive for them. Besides, some employers might decide to exploit a child because most children do not have an exposure about their rights and benefits related to the job and compensations if the work is in an unsafe environment. Hence, these cost savings might make firms to choose a child labor than an adult worker. It might not be easy to see a remarkable reduction in child labor in the existence of such companies which depend on child work and child producing goods. Though the market-related child labor and its causes have been investigated by some empirical researchers, the studies on the causes of non-market related child labor (like farm work, fetching water, collecting wood and other domestic chores) are hardly investigated.
It is not uncommon that most rich households who own a lot of livestock and land to demand more child labor in their farm works or other domestic chores and withdraw their child from schools. These types of decisions by the wealthy families might nullify the poverty as the leading cause of child labor argument which is stated repeatedly in the child labor theories and empirics. The reason for the wealthy household to choose child labor could be because the wealthy family believes that they have plenty of resources to be inherited to their child compared to the future return of investing in their child. Hence, they might see the return to education against the resources they could inherit to their child while ignoring other human capital development aspects. Such kinds of perceptions and decisions are difficult to observe, but it is easy to imagine that they can apparently bring a significant variation in child labor.

It has been common to conduct a series of meetings between parents and government officials to discuss the benefit to child schooling while the results of the meeting turned out to be devastating. It was common until recently, to observe parents refuse to send their child to school even when they confronted with the responsible officials in Ethiopia. To the contrary, it was common to see a child from a household who owned none or less livestock or land to be involved in less child labor but attending school.

Consequently, concluding poverty as the leading cause of child labor might be biased. In addition to this, the differences on adopting a drought coping strategies, socio-cultural and economic differences among countries might have a different way of perceiving and solving the child labor problem. Consequently, generalizing the research findings, for example, from one part of the world related to the causes of child labor might lead to a biased and wrong policy options to other countries.

Shah and Steinberg (2017) find that a good monsoon, which leads to an increase in agricultural productivity and to higher wage earnings for both the parents and their child, was associated with a higher demand for a child labor in rural India while reported less child labor in the drought years.

Several other studies also find that there is a significant positive association between child labor and the wet seasons. Soares et al. (2012) find that a positive production shock, which is similar to good monsoons, had significantly increased the probability that children only work and not...
attending school. This might be likely to happen if the child or its patents perceive that the opportunity cost of children's time at school is high when a higher wage earning possibility exists due to the good monsoon. Their finding indicates that drought (adverse shock) associates with a low child labor incidence.

Bhalotra & Heady (2003) find that children of the land rich households are most of the time likely to be at work vice versa. Their finding, however, is opposite to the positive association between poverty and child labor supply. Their result seems convincing in a case where a wealthy family demands more child labor to assist them on their massive farmlands or to substitute adults on other domestic activities when the adults involved in farm work. This implies that poverty is not the main reason for a child labor. It also means that child labor has a positive association with land size. Basu et al. (2010), however, argued that there is a negative relationship between a particular size of a land wealth of a household and a child labor.

There are other findings which are in opposition to the negative association of child labor and drought shock (or bad monsoon). Akresh et al. (2012) and Beegle et al. (2006) find that experiencing negative rainfall shock (drought) was associated with an increased child labor and a higher dropout from school. Households who were affected by a drought tend to increase their use of child labor. They also find that families with relatively high asset holdings were able to cope with the shocks and they demand less child labor.

This could be due to the case that a drought negatively affects the economic activities of the family so that they have to demand child labor to secure at least their subsistence consumption level. The inability to sustain their consumption above the subsistence level might force them to use more child labor as a drought coping strategy especially in countries which lack functional credit and loan markets. The finding by (Beegle et al. 2006) is consistent with the child labor theories which argued about the existence of a direct relationship between poverty and child labor supply.

From the existing research findings related to different climate shocks (for example drought) and child labor, one can understand that there are still disparities. Besides to this, using a child labor research finding from an industrialized country perspective might result to sort of biased policy decisions if it is implemented directly in the least developed countries vice versa. These
differences might happen because of the differences in the perception of households towards child labor and the drought vulnerability and adoption of coping strategies by countries.

The inconsistent empirical findings of the child labor and drought relationships plus the urgency of child labor problems have motivated me to conduct this research. A research finding related to the effect of drought on a child labor in the rain-fed and subsistence agriculture dependent society is expected to have a vital importance for both empirical contribution and customized policy options.

To the knowledge of the researcher, very few empirical studies have been conducted by others on the effect of drought (adverse shock) on child labor. The existing research findings are mostly cross-sectional and mainly focused on the child labor incidences without actually observing the child’s working hours in the drought and out of the drought seasons. Therefore, this study is conducted to empirically test the effect of households perceived drought shock on child labor (or hours of work). I have employed a three-round panel data (2006-2013), which had been collected by the UK data-service, Young Lives from Ethiopia, and contribute to the existing theoretical and empirical child labor and related literature.

1.2. Objectives of the study

1.2.1. General objective:
The general objective of the study is to investigate the effect of a household’s self-reported drought experience on child labor using a fixed effect panel estimation model.

1.2.2. Specific objectives

1. To examine the effect of household’s perceived drought shock on the use of child labor.
2. To analyze the effect of drought on child labor by including time variant controls.

1.3. Hypothesis

H0: child labor has no significant relationship with the household’s perceived drought shock.
Chapter 2: Related literature review

2.1. Theoretical literature on the effect of drought on child labor

There is an increasing theoretical and empirical research related child labor and its determinants. There are theories and conceptual models that explain the relationship between consumption, hours of work by a child and child’s leisure, poverty, and wage and nonwage income variables among others.

Reviewing and using the existing child labor-related theories, criticizing their deficiency (if any) and showing the missing part is believed to enrich the current theoretical literature on child labor.

The Theoretical literature, not many though, to date have been written on the effect of poverty on child labor supply provided that there is functional labor market. Some of them lacked to incorporate the causes of the nonwage child work and the effect of drought (or adverse climate shock) on child labor, especially in the developing countries and subsistent agricultural societies.

There are essential theoretical models on child labor, dating back to the economics of child labor models of (Basu and Van, 1998). This model treats the production and utility functions of a child as inseparable from the household production and consumption functions, i.e., unitary model. They developed the basic child labor model based on the luxury and substitution axioms coupled with the central idea that the parent makes child labor supply decision. Their luxury axiom deals with the use of child labor by a particular household in the case where family’s none child labor income goes down.

Consequently, a decrease in income leads to use of child labor while an increase in income leads to use of leisure and schooling through an income effect. Their substitution axiom deals with firms substituting adult and child labor based on the child’s effective wage per adult equivalent, i.e., if the effective wage for a child is cheaper than the adult then the firm will tend to employ the child vice versa.

Basu and Van (1998) claim poverty as the primary determinant of child labor which they believe that children of the wealthy family seldom work even on developing country standards. However, their theoretical model is rarely consistent with the contemporary empirical pieces of
evidence. The reason why they hardly get support from the empirical literature might be due to the very idea that the empirical researchers' reasonable investigation to the causes of child labor on both wage and nonwage works and other domestic chores of the developed and developing countries and under differing market conditions. For example, there are cases where children of land rich (a proxy for a store of wealth) family work more than land-poor families (Bhalotra and Heady, 2003), which contradicts to the theoretical claim by (Basu and Van, 1998).

Boozer and Suri (2001) come up with a theoretical model which drives from (Basu and Van 1998), by incorporating a rainfall variable. They took into account the effect of rainfall and its impact on child labor and schooling decisions than only relying on poverty as a determinant of child labor supply. Their theory is by far nearer to the contemporary empirical research findings where income and labor markets are often affected by internal and external shocks.

Boozer and Suri (2001) claim that a high rainfall decreases the marginal productivity of the household and the child labor. However, they did not see the possibility that drought can limit both the child and parent’s productivity while rainfall might help them to increase their production and productivity, especially for agriculturalists. (Shah and Steinberg, 2017) find that child labor decreases in a drought year while it rises in the rain (or monsoon) season.

Brown et al. (2002) discuss a child labor supply in a competitive market. He argues that an increase in the father’s wage leads to a rise in the price of his leisure. If the leisure of the father and the child education are substitutes, then the father’s leisure leads to a substitution of the child’s education or non-work activity. He extends his argument that an increase in the wage of a child increases the opportunity cost of time spent school. These two arguments indicate that a wage rise for both the father and the child leads to a child work.

However, if the family perceives that child education or leisure is normal good and wage of the father increased at the same time, then child work tends to decrease while child leisure or education increases. This theory, however, might lose its credibility when the market is no more perfectly competitive, the types of jobs are nonwage works and if the child works at home and other domestic activities than working for a wage.
Current negative rainfall shock (or drought) is expected to affect the household and child productivity to go down and leads to a reduction in child labor and overall household labor supply especially in rural areas where households depend on rain-fed agriculture to a more considerable extent. Therefore, some part of the (Boozer and Suri, 2001) model is adopted to formulate the conceptual model while drought is chosen instead of high rainfall in this study.

2.2. Empirical literature on the effect of drought on child labor

Although the theoretical literature shows poverty as the primary source of child labor, the direct link between adverse climate shocks and child labor has not been explored remarkably in both the theoretical and empirical research. Besides to this, it was not clear in some of the findings that whether the type of adverse shock under study was a temporary or a persistent one. A one period study on the effect of income shock on a child labor might not have the same effect if the adverse shock has persistently occurred for some time. Households might make a necessary adjustment to adverse shocks that have been happening persistently so that the child work might not be genuinely estimated if the study is cross-sectional. In addition to this, the previous year’s shock might still have an effect on the current child labor supply.

The livelihood of many agricultural households in the least developed world, especially the smallholder farmers, are dependent on the timing and quantity of rainfall which is not predictable by the families (Gray and Mueller, 2012). It indicates that the negative rainfall (or drought) season has a significant impact on the household’s time allocation to solve its production and consumption problems simultaneously.

Using the same Young Lives data used for this study, (Hyder et.al. 2016), studied the effect of climatic shocks on child school enrollment in Ethiopia. Using a probit estimate of community-level shocks, they find a negative impact of drought shock on child school enrollment reflecting the income effect of drought. Seeing the competing nature of child work and school enrollment, the adverse effects of drought on schooling might indicate that drought affects a family to use its child for work than to send it into school.

Serna (2011) finds that drought affects children which leads them to contribute to their family’s income and other duties. Children were withdrawn out from school in the drought season for child work. He finds that in the drought season children had been getting small jobs to sustain
their family needs and traveling a long distance to fetch water. This finding is consistent with the argument that drought leads to more child labor supply and less to school attendance (enrollment).

Shah and Steinberg (2012), using the ASER data and close to 3 million rural children studied on whether drought could improve human capital. They had seen the effect of drought based on the income and substitution effects. Using the current period’s household reported drought data, they find that current drought rate had an increasing effect on the test score and attendance rates of the child. However, they find a lower test score and a high likely dropout report by the students in the positive rainfall season. It indicates that at the time of drought years, children were substituting work with schooling, i.e., they attend their school because there is less work opportunity. In addition to the effect of drought on education, they also tested the response of parents and child work in drought years.

Consequently, they find that both parents and child were less likely to be employed. Even if they get a job, they will only get a lower wage in the drought years vice versa. Their result seems consistent with the child work in the rural areas and the subsistence agricultural society while it hardly explains the child labor involved in industries and the urban areas. Though all children might experience the drought, the effect of drought might be seen visible more in the rural and agriculture-dependent societies who are expected to be less employed in the drought season than the urban residents and market wage earners.

Bock (2002) also finds that during the agricultural production season more child work had been demanded and school attendance reduced for both boys and girls. During the harvest season, girls had been working through the whole week especially in processing millet for the family while boys were helping the family at the farmlands in harvesting. It indicates that the variation in agricultural productivity due to some shock (e.g., drought) has a differential gender effect in working hours. Consequently, drought leads to less working hours for both boys and girls. However, girls were observed to be working throughout the week which might affect their schooling time while boys were found to be helping their parents at weekends and early morning, when milking and sending cattle to the bush takes place.
Guarcello et al. (2010) find that exposure to drought strongly influences households decision to use child labor. They find that use of child labor increases as a response to drought. They, however, indicate that if households have access to some coping mechanisms like access to credit or insurance, then child labor tends to decrease while child schooling tends to increase even during the drought season.

A drought has a crowding out effect on the households farm work activities. However, productive public safety-net works, which aimed at protecting households from drought and other shocks, might have a significant contribution to the family in generating income when drought dried their work opportunities, especially for the agricultural dependent society (Edmonds, 2006). Public safety-net, on top of its usage as a coping strategy to drought shocks, might bring a significant reduction in child labor which needy families use it as an income generating mechanism during the time of drought (Serna, 2011).

Hoddinott et al. (2009) studied the impact of a productive safety-net program on child schooling and child work which devoted to farming work or other domestic work. They argue that the opportunity cost of the child schooling varies by gender of the child and among different age groups. Public safety-net programs act as a form of employment insurance especially for the poor. However, public safety-net, other than other social protection programs, demands high labor requirement which might alter the intra-household allocation of labor and the child and adult substitutions which is consistent with the substitution axiom of the child labor theory of (Basu and Van, 1998).

Hoddinott et al. (2009) then find that family’s participation in public safety-net works had significantly reduced child labor. They find that participation in public works leads to a reduction in agricultural labor hours and a reduction in domestic labor hours for the older and younger boys respectively. They also tested whether a cash transfer affects child labor or not and schooling. They find that a regular cash transfer had a significant increase in school attendance rates and a substantial reduction in total hours worked for the older and young boys respectively. However, they find that participation in public safety network had an increased child labor and a lower school attendance for the young girls. A more significant cash transfer to the family, however, had a substantial reduction in labor hours and increase in school attendance for the older girls.
Regarding to birth order, child labor and schooling, De Haan et.al (2014), investigated whether family treat their children differently on the basis of the financial resources they allocate to their respective children and she find that earlier born children stay longer in school and participate in less child labor because parents spend more money on them and vice versa. Alvi and Dendir (2011) find that earlier born child is more likely to attend school than its younger siblings, especially in rural areas, in Ethiopia. However, (Shah and Steinberg (2017) and Dammert (2010)), find that a child, especially earlier born child, was highly likely to engage in child labor. It might be true that the family needs the child to assist them on the farm and domestic works mainly in the monsoon season as the opportunity cost of schooling increases in a good rain season vice versa.

When households experience a drought, they might look for a credit to smooth their consumption. Hence, loan is expected to have a significant impact, especially for the drought-vulnerable poor households to cope up in the drought season. Dehejia and Gatti (2002) find a negative relationship between child labor and access to credit by the family. They argued that households use significantly more child labor in response to adverse shock (example drought) in countries with less developed financial markets. It indicates that parents who are able and get access to credit to fulfill their current financial shortcomings could reduce the labor supply needed from their respective child. However, in the absence of the ability and access to credit, parents might only be left with a child labor as drought coping strategy to fulfill their household problems.

Fitzsimmons (2002) finds that in rural areas an adverse shock has a direct relationship with lower schooling for children in general, and the effect is more substantial in villages without formal credit. As there is an expected tradeoff between child work and schooling time, one can see that it is highly likely to observe more child work in rural areas in general and the villages without formal credit access in particular.

2.3. A conceptual Framework on the effect of drought on child labor
This section consists of a conceptual framework for the parent’s decision-making process in using child labor when they perceive drought shock.
This conceptual framework focuses on the behavioral factors, which affect the determination of hours of work of a child by a household. The critical factor considered in the decision of hours of work by a child was perception towards drought shock which is expected to induce a variation in a child labor (or hours of work by a child).

If current period drought is independent of drought in the previous period, then it will induce mainly a substitution-effect of decreasing the demand for child labor on the productivity side. As a result, drought influences the marginal productivity of the child to go down. However, if drought patterns are quite persistent, then the effect of current drought might affect the current productivity and next period productivity.

If the income effect dominates the substitution-effect, then child labor will increase in the drought period vice-versa (Basu and Van, 1998). Hence, if the substitution effect dominates to the income-effect, then child labor will tend to decrease in the drought period while it increases in the rain season (harvest season). The second argument of (Basu and Van, 1998) is consistent with (Boozer and Suri, 2001), who find that current rainfall induces a pure substitution-effect on child labor.

A drought can be regarded as persistent if it exists for an extended period and it might not be random anymore for the next consecutive time periods. A persistent drought is expected to affect both production and consumption function of the households. However, if the drought under consideration happens only temporarily and is random, it is believed to have an immediate effect on production and labor supply than on consumption.

A drought is expected to create a downward jump in the productivity of the child who is subject to work. It is also likely to affect the marginal productivity of a child to decline especially for the child working in agricultural activities. But it, drought, could have an insignificant effect on the child working at home chores, industrial and service sector since the drought has no direct and immediate effect on these types of job markets.

Due to these diverse nature of work activities, households perceptions towards the use of child labor and their attitude towards taking drought risks; drought might bring a variation in working hours across individuals and time. The rules and regulations related to child labor and the poverty and drought coping strategies taken by the government across different time periods
might also show a variation in working hours within individuals. Besides to this, drought is believed to be exogenous and create a considerable substitution effect between child labor and leisure and flashes a signal for policy options in child labor reduction or child school enrollment and enhancement issues.

Therefore, the empirical model that is believed to represent these issues is a static model of which drought variable enters into the production function. The other reason why a current drought is preferred to persistent drought to see its effect on hours of work is that the latter is believed to suffer from omitted variable bias for the fact that its lagged drought value might have an impact on some actions of a household or a child.

The conceptual framework of this study is formulated considering by adopting the (Wälti, 2003) model. This models deals with a one good one shock real business cycle model. The main assumption implies that utility as a function of consumption and leisure is strictly increasing, strictly concave, and a continuously differentiable.

Wälti (2003) argues about child labor using the labor effort as an input to production (he has no capital or any other input). He explained that a temporary adverse shock shifts the production function downwards. The adverse shock leads to a wealth and substitution effects. Since the negative shock is short-lived, the decline in wealth must be small and brings a little decrease in consumption. Moreover, current aggregate leisure decreases slightly and, equivalently, current aggregate work effort, \( N \), increases somewhat. Therefore, the small decline in wealth raises work effort.

As the marginal productivity of labor in the current period decreases temporarily due to the drought, contemporary leisure becomes cheaper relative to consumption in the current time. However, present consumption and present work effort will decrease while current leisure rises, i.e., the Static substitution effect between leisure and consumption exists.

For simplicity, assume that the production function is affected by drought and other inputs except labor are suppressed for simplicity. In this case drought shifts the demand for labor downwards i.e substitution effect dominates the income effect.
Therefore, it can be understood from the (Wälti, 2003) model that the adverse shocks affect the current productivity of labor to go down. Hence, the household puts more work effort to fill the consumption gap and reduce the leisure time accordingly. Consequently, it can be said that drought leads to more hours of work by the child especially in the absence of formal saving and credit markets which they could reduce the prevalence of child labor during drought season.

The econometric model derived from this theoretical and empirical literature is discussed in the methodology section. The model specification, choice of control variables and estimation techniques are also incorporated.
Chapter 3: Methodology

3.1. Study Area Description

This study is conducted using a three-round panel data from Ethiopian households. Ethiopia is ranked 12th regarding population in the world today. The current population of Ethiopia, according to the latest United Nations estimate, is estimated to be close to 105 million and out of this 20.2% of the population is urban. The median age of Ethiopians is 18.8 years (worldometers, 2017).

According to the data accessed from the report (UNICEF, 2016), an estimated 150 million children are involved in child labor globally. The prevalence of child labor is highest in sub-Saharan Africa which Ethiopia is not an exception. According to (UNICEF, 2012), out of the total Ethiopian children aged 5-14, 27.4% of them were working.

Children in Ethiopia often begin to engage in child labor at their early age and they, on average, work 29-30 hours in both domestic and market-related activities (Arjun and Assefa, 2009). Other researchers also find that there were many children involved in many forms of work, like in agriculture, service, industries, shops, marketplaces and other domestic chores and even begging on the street in Ethiopia (Abebe, 2008).

A study in Ethiopia reveals that both poverty constraints and income opportunities play essential roles in the decision to use child labor or not. Cockburn (2001) finds that work and school conflict considerably but not entirely. In rural parts of the country, household poverty is affected by the large family size and lack of farmland which leads to low family income.

Hence, parents tend to encourage and even sometimes force their children to enter the labor market in their early ages to enhance the household income and sustain the family’s consumption expenditures. Other findings also support the direct relationship between poverty and the use of child labor. at the same time, they also argue that the use of child labor on the farm and off-farm activities and in other sectors of the economy has become not a matter of choice because of the extreme poverty (Woldehanna et al., 2005).

In Ethiopia, children were involved in work activities and with various forms even when they were too young (5 years old). At the country level, 61.44% of children in the age range of 5 to 14
participated in work with similar participation rate across gender. Other findings also support this statistics that the participation rate is high in the rural area where 63.52% of children involved in child labor as compared to the 46.09% of children participated in the urban parts of Ethiopia (Macro, 2006).

3.2. Method/s of Data collection
I employed a secondary data collection method for this study. The researcher has accessed the secondary data from the UK data service, Young Lives datasets. The researcher has also made a careful filtering, cleaning, and organizing of the necessary secondary data that is believed to fit the purpose and model specification of the study.

3.3. Data and sources of Data
The household and child level data in this study comes from Ethiopia’s national household survey for the years 2006-2013 administered by the UK data service, Young Lives program, once in a three years time.

This Young Lives secondary data is particularly suitable for the topic under study as it uniquely combines the necessary selection of determinant factors for the basic child, household and community level characteristics with a rich child-level data that contains an unprecedented level of detail. This combination has helped me a lot to efficiently work with issues related to the effect of drought on child labor than has previously been possible in some empirical research works by others. Investigating the impact that a drought might have on child labor was easy because of the precious data collected by the Young Lives

3.3.1. Statistical description of the data
Table 1: Demographic characteristics of the child from three round surveys

<table>
<thead>
<tr>
<th>child and household characteristics</th>
<th>Round1 mean</th>
<th>Round2 mean</th>
<th>Round3 mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age of child</td>
<td>12.07</td>
<td>15.03</td>
<td>18</td>
</tr>
<tr>
<td>Household size</td>
<td>8.05</td>
<td>6.82</td>
<td>9.54</td>
</tr>
<tr>
<td></td>
<td>sd 0.003</td>
<td>sd 0.002</td>
<td>sd 0.002</td>
</tr>
<tr>
<td>Source: Author’s computed statistics from UK data service, Young Lives data</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 1 shows the average age of the children sampled in each round. It seems that the sample is taken from similar age groups in every round as the standard deviation looks very small. However, the average household members living in one family were big enough. The standard deviation of the family size seems small between individuals while the difference looks significant when compared to the survey rounds. The difference in the size of household across time could be due to a newborn or a death of a family member.

**Table 2: Gender composition of the child over the three rounds of the survey**

<table>
<thead>
<tr>
<th>Child and household characteristics</th>
<th>Round1</th>
<th>Round2</th>
<th>Round3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex of Child</td>
<td>male</td>
<td>female</td>
<td>male</td>
</tr>
<tr>
<td>51.67</td>
<td>48.33</td>
<td>50.91</td>
<td>49.09</td>
</tr>
</tbody>
</table>

Source: Author’s computed statistics from UK data service, Young Lives data

Table 2 shows the percentage of the child included in the survey by sex ratio. It seems that the sex composition of the sample of children is relatively equal. It then helps to see if there is gender bias towards child labor without worrying about the size of one sex group over the other in the sample representation.

**Table 3: Average hours of work per day in the households’ self reported drought season**

<table>
<thead>
<tr>
<th>Self reported drought experience</th>
<th>Round1</th>
<th>Round2</th>
<th>Round3</th>
<th>Overall average</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>4.25</td>
<td>2.91</td>
<td>6.92</td>
<td>4.69</td>
</tr>
<tr>
<td>Yes</td>
<td>5.32</td>
<td>3.35</td>
<td>6.46</td>
<td>5.04</td>
</tr>
</tbody>
</table>

Source: Author’s computed statistics from UK data service, Young Lives data

Table 3 shows the cross-tabulation of the average hours worked by the children when their respective household perceives the existence of drought shock and without. Children seemed to work more hours, on average, when their parents feel the drought shock in the first two survey rounds while there is a small decrease in the third round. But the grand average of hours of work for the three rounds shows us that children worked more when households reported there was an existence of drought. The reason for the increase in the average hours of work might be due to
the case that children might be withdrawn from schools so that the time that was supposed to use for schooling diverts to child work in some domestic, farm work and other paid work activities.

**Table 4: Average hours of work per day over the survey rounds by sex of the child**

<table>
<thead>
<tr>
<th>Sex of the child</th>
<th>Round1</th>
<th>Round2</th>
<th>Round3</th>
<th>overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>4.47</td>
<td>2.85</td>
<td>6.18</td>
<td>4.50</td>
</tr>
<tr>
<td>Female</td>
<td>4.69</td>
<td>3.09</td>
<td>6.14</td>
<td>4.64</td>
</tr>
</tbody>
</table>

Source: Author’s computed statistics from UK data service, Young Lives data

Table 4 shows average hours of work by sex of the child in the three survey rounds. On average, female seemed to work more every survey rounds. The descriptive statistics result might indicate that female child bears the most of the workload of the family and spending more on child work than the male counterparts. This is consistent with the empirical literature which they argue that female child is likely to withdraw from schools due to some safety problems of sending a girl to school and the early marriage perceptions of the parents. The safety problems of sending a female child to school and other cultural issues might affect her parents to let her stay at home and work more hours. The negative barriers of sending a girl to school can imply for the more average hours of work by her on top of the family’s interest to get a support inside and outside the home like at the farmlands and family businesses from a child.

**Table 5: Average hours of work per day by the sex and residence of a child**

<table>
<thead>
<tr>
<th>Sex of the child</th>
<th>Urban</th>
<th>Rural</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>male</td>
<td>3.22</td>
<td>4.14</td>
<td>3.68</td>
</tr>
<tr>
<td>female</td>
<td>3.46</td>
<td>4.38</td>
<td>3.92</td>
</tr>
<tr>
<td>Average for both sex group</td>
<td>3.34</td>
<td>4.26</td>
<td>3.8</td>
</tr>
</tbody>
</table>

Source: Author’s computed statistics from UK data service, Young Lives data

Table 5 shows the average hours of work by gender and area of residence of the respective children. The average hours of work of a male child in a rural area are observed to be more than their urban counterparts. It is also similar to the female child who lives in rural areas worked to be more than the urban female child. The reason for the urban children working less than the rural once could be due to the case that their parents have better access to information on child’s
future investment, the availability of institutions working on reducing child labor which they mostly exist in urban areas and the urban parent’s lower vulnerability to drought. It might indicate that the society living in rural areas have lower access to support services related to the cost of child labor and the return to child investment.

Table 6: Average hours of work by a child per districts and survey rounds

<table>
<thead>
<tr>
<th>District(Region)</th>
<th>Round1</th>
<th>Round2</th>
<th>Round3</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Addis Ababa</td>
<td>2.75</td>
<td>2</td>
<td>7.58</td>
<td>4.11</td>
</tr>
<tr>
<td>Amhara</td>
<td>4.95</td>
<td>2.78</td>
<td>6.50</td>
<td>4.74</td>
</tr>
<tr>
<td>Oromia</td>
<td>5.20</td>
<td>3.08</td>
<td>6.02</td>
<td>4.76</td>
</tr>
<tr>
<td>SNNP</td>
<td>4.85</td>
<td>2.83</td>
<td>5.17</td>
<td>4.28</td>
</tr>
<tr>
<td>Tigray</td>
<td>4.52</td>
<td>3.95</td>
<td>7.23</td>
<td>5.23</td>
</tr>
<tr>
<td>Total</td>
<td>4.45</td>
<td>2.92</td>
<td>6.50</td>
<td>4.62</td>
</tr>
</tbody>
</table>

Source: Author’s computed statistics from UK data service, Young Lives data

Table 6 shows that, on average, children from Tigray region, which are located in the northern part of Ethiopia have worked more hours compared to the rest of the children living in the other areas in the three survey rounds. However, the children from Addis Ababa, the capital city of Ethiopia, worked less than the rest of the child in the rest of the regions over the three survey rounds. This result is consistent with the finding by (Central Statistical Agency, 2012). The reason for the Tigray district’s child was working more hours, on average, could be because the northern part of Ethiopia is the place where it is relatively drought vulnerable area than the rest so that children were forced to look after jobs to sustain their family’s needs. In contrast to this, the reason for the children in Addis Ababa worked less than their counterparts could be due to the case that it is urban and households are less prone to drought shocks in addition to the attention given by governments and institutions to control child labor in urban areas than mostly rural-dominated regions.
Table 7: child’s average hours of work by type of work

<table>
<thead>
<tr>
<th>Type of work</th>
<th>Round1</th>
<th>Round2</th>
<th>Round3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Farm work</td>
<td>44.87</td>
<td>19.85</td>
<td>45.14</td>
</tr>
<tr>
<td>Domestic tasks</td>
<td>2.56</td>
<td>44.99</td>
<td>1.74</td>
</tr>
<tr>
<td>Child care or care of elders for HH</td>
<td>5.13</td>
<td>22.04</td>
<td>0.37</td>
</tr>
<tr>
<td>Making or collecting things for sale</td>
<td>3.85</td>
<td>0.92</td>
<td>10.46</td>
</tr>
<tr>
<td>Selling goods or services</td>
<td>20.51</td>
<td>2.44</td>
<td>17.16</td>
</tr>
<tr>
<td>Working for wage in non-agricultural activity outside the household</td>
<td>7.69</td>
<td>4.27</td>
<td>22.02</td>
</tr>
<tr>
<td>Other</td>
<td>15.38</td>
<td>5.50</td>
<td>3.12</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

Source: Author’s computed statistics from UK data service, Young Lives data

Table 7 shows the percentage of children worked under different types of jobs. Children worked mostly on farm work, domestic tasks, and childcare or care of elders in the household in three of the survey rounds while they worked less on making or collecting things for sale respectively. It shows that children were exploited mostly on non-wage work activities. These types of work activities are exercised mainly in rural areas and agricultural societies.

Table 8: A household self reported data related to the types of shocks experienced in each survey round

<table>
<thead>
<tr>
<th>Type of Shock happened</th>
<th>Round 1</th>
<th>Round 2</th>
<th>Round 3</th>
<th>Sum over three rounds</th>
<th>Average over three rounds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household experienced this type of shock</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Drought</td>
<td>680</td>
<td>300</td>
<td>614</td>
<td>360</td>
<td>806</td>
</tr>
<tr>
<td>Large increase in input prices</td>
<td>683</td>
<td>297</td>
<td>618</td>
<td>356</td>
<td>813</td>
</tr>
<tr>
<td>Crop failures</td>
<td>765</td>
<td>215</td>
<td>715</td>
<td>259</td>
<td>743</td>
</tr>
<tr>
<td>Event</td>
<td>1st</td>
<td>2nd</td>
<td>3rd</td>
<td>4th</td>
<td>5th</td>
</tr>
<tr>
<td>-----------------------------------</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
</tr>
<tr>
<td>Illness of Child’s mother</td>
<td>782</td>
<td>198</td>
<td>761</td>
<td>213</td>
<td>795</td>
</tr>
<tr>
<td>Illness of Child’s father</td>
<td>829</td>
<td>151</td>
<td>828</td>
<td>146</td>
<td>836</td>
</tr>
<tr>
<td>Too much rain or flood</td>
<td>847</td>
<td>133</td>
<td>850</td>
<td>124</td>
<td>849</td>
</tr>
<tr>
<td>Birth/new household member</td>
<td>821</td>
<td>159</td>
<td>890</td>
<td>84</td>
<td>896</td>
</tr>
<tr>
<td>Enrollment of child in school/having to pay school fee</td>
<td>884</td>
<td>96</td>
<td>864</td>
<td>110</td>
<td>871</td>
</tr>
<tr>
<td>Pests or diseases that affect livestock</td>
<td>937</td>
<td>43</td>
<td>873</td>
<td>101</td>
<td>891</td>
</tr>
<tr>
<td>Erosion, Cracks or landslides</td>
<td>906</td>
<td>74</td>
<td>938</td>
<td>36</td>
<td>879</td>
</tr>
<tr>
<td>Large decrease in out prices</td>
<td>919</td>
<td>61</td>
<td>929</td>
<td>45</td>
<td>882</td>
</tr>
<tr>
<td>Death of Child’s father</td>
<td>933</td>
<td>47</td>
<td>936</td>
<td>38</td>
<td>884</td>
</tr>
<tr>
<td>Pests or diseases leading to storage loss</td>
<td>950</td>
<td>30</td>
<td>953</td>
<td>21</td>
<td>903</td>
</tr>
<tr>
<td>Death of Child’s mother</td>
<td>956</td>
<td>24</td>
<td>957</td>
<td>17</td>
<td>900</td>
</tr>
<tr>
<td>Other event</td>
<td>975</td>
<td>5</td>
<td>967</td>
<td>7</td>
<td>886</td>
</tr>
</tbody>
</table>

Source: Author’s computed statistics from UK data service, Young Lives data

Table 8 shows the percentage of households perceived to be affected by different types of shocks. Different families might have different kinds of experiences and attitude towards these adverse shocks based on their overall environmental observation or through the information from national metrology organization. All these adverse shocks are believed to contribute to the household’s livelihood negatively but differently. The differences in the perception of these shocks might bring a variation on hours of work by a child. The Table shows that a drought, a large increase in input prices and crop failure are the top three and most frequently happened shocks to most of the households in the three round of the survey. Both drought and crop failure are likely to occur naturally where the families have less to do with preventing themselves from these natural shocks. However, the increase in input prices seems to come from a human action
especially from a government intervention since most of the inputs like fertilizer and other technologies supplied to the farm households by the government.

A drought dummy variable is included in the panel regression analysis to represent the effect of the perception of a household or child towards drought shock on the percentage of average hours work per day by a child. Most of the self-reported shocks in (table 8) are considered to be idiosyncratic where they could have a different effect on child labor than the common shocks like drought. However, if the perception of households towards drought is different compared to others which may exist due to their difference in their attitude towards taking risk and experiences, then average hours of work by a child might vary between children and across time periods. Hence, part of a drought shock might also be entered as an idiosyncratic shock in the household’s production and consumption functions which leads to a variation in hours of work or use of child labor decision.

3.4. Sample and Sampling
This study's sample consists of all children who involved in any work: family-owned business or farm, market-related and domestic chores, either for a wage or unpaid family workers. All children whose hours of work data were available in three of the survey rounds except children who have missing data on hours of work and drought in the Young Lives dataset are considered for the fixed effect panel data estimation in this study.

The outcome of interest is by how much hours of work of a child might change when the household perceives differently about the exogenously existing drought shock across years and between other families. The total number of working days and the hours worked per week were used to calculate the average hours of work per day by a child. The hours of work consists of hours spent on any kinds of work, i.e., paid work, unpaid work, farm work and other domestic chores per day. The unpaid works undertaken by the child in the sample includes cattle herding, milking cows, and assisting on the family farm, fetching water, collecting wood or being involved in other family business. Children’s responsibilities concerning domestic tasks include fetching water, collecting firewood, house cleaning, cooking and caring for others in the household.
The relevant data about the time spent on each work activities per week was recorded and made available by the UK data service, Young Lives program. The households in the sample were predominantly agricultural, and they are vulnerable to substantial seasonal fluctuations due to some adverse natural shocks like drought. A drought is a common shock at least for one village or district and a country at large. However, due to several factors, the perception towards the drought shock might not be the same for every household. In this study, a household’s self-report about the present perceived drought is taken into consideration to see its effect on the variation of hours of work by a child.

The sample includes all old cohort children belonging to the age group (12-18) for whom hours of work (for both domestic and market-related work) and the response to the drought dummy are non-missing. The regression, based on the model explained in section 3.5 below, is run only for the children without missing values in either the hours of work or drought dummy. Data for a single child is observed in every survey round from the whole family. Therefore, there is only one observation from the entire family.

3.5. Empirical model specification and method of analysis
This study examines the effect of a household’s self-reported drought shock experience on child labor. This study uses a panel data analysis due to the repeated observations over different time periods. Applying a panel data regression model, especially fixed effect model, gives a more consistent and efficient estimate than the simple OLS regression because the first controls the unobservable that differ between entities but constant within the units over time and unobservable that varies over time but stays constant across individuals.

Stock and Watson (2012) defines panel data analysis as an econometric technique which combines cross-sectional and time series data. An estimation model that can control for missing time-invariant un-observables i.e. factors that vary between entities but constant over time is a suitable tool for this study. This empirical approach and model specification adopted in this study is consistent with some previous similar studies like (Beegle et al., 2006).

The general model specification of the study is presented as follows: I have employed the following empirical specification to investigate the effect of household’s or a child’s current
year’s drought perception on child labor. In this study, child labor refers to the child’s average number of hours worked per day.

Hsiao (2014) argues that the benefit of using panel data is that the possibility of modeling more realistic behavioral hypothesis. For example, the perception of the parent or the individual in deciding whether to use child labor or not in the drought season might be a result of varying behavioral processes between individuals but constant over time. The differences might arise due to the differences in motivational factors and ability characteristics of the individual which the data for those specific variables are missing. In addition to this, the average hours of work (i.e., the outcome variable) might be observed only if the household decides to use child labor. In the existence of such sample selection problems, using OLS leads to a biased estimate.

Therefore, sample selection models like Heckman two-step model might be the best option to use to account the selectivity bias that arises when the residual of the hours of work equation is correlated with the residual of the selection equation. For example, the selection into the child labor might depend on the perception of the household towards drought and risk-taking behavior. Because the risk-taking behavior of the individual is unobserved, it will go to the residual. Therefore, there will be an endogenous selection and a biased estimate. This endogenous selection bias might be corrected by including controls to the regression or employing Heckman two-step selection models.

However, there should be data on the explanatory variable for both the selected and non-selected observations. Even though, there is a suspect of endogenous selection bias in deciding to use child labor, the absence of data for the potential controls, especially for the un-observables, makes OLS estimation model out of choice. Besides to this, Heckman two-step selection models could only help to mitigate this selection bias if the study under consideration was cross-sectional. Therefore, an estimation model that accounts the un-observable heterogeneity between individuals over a longitudinal has to be applied.

Therefore, a panel data models and/or an extension to Heckman selection (i.e. two estimation procedures that correct in the presence of endogenous regressors) are suitable (Semykina & Wooldridge (2010) and Wooldridge (1995)).
Hence, panel data analysis is preferred because it provides an accurate inference of the parameters and uncovers the dynamic relationships by pooling the child level data over several time periods. A panel data model is specified, and the suitable panel data estimation model is chosen after conducting a statistical test and based on the theoretical and empirical pieces of evidence. A pooled OLS panel data model is specified in log-linear form as:

\[
\text{Lnhours} = \beta_0 + \alpha_1 \text{drought}_{it} + X_{it}'\beta + \varepsilon_{it}
\]  

(1)

Where the dependent variable represents the log of average hours worked per day by a child in the survey round \(t\), \(X_{it}\) represents a set of controls which include child (age), age squared of a child and household characteristics (age of the household head, family size, wealth index of the household, access to credit and land ownership) characteristics at the survey round \(t\) and \(\text{drought}_{it}\) is a dummy for the perception of drought by the household at the survey round \(t\). The drought is the important explanatory variable which is assumed to be exogenous to the population.

The drought dummy is measured based on the individual’s self-report about his/her perception towards the drought shock but not by the loss of income due to drought shock because the latter is likely to suffer from measurement error (Alvi and Dendir, 2011). Otherwise, the explanatory variable might be suffered from measurement error if households answer differently about the existence of drought while the drought exogenously exists for all families at least in the same district or country. Hence, drought is assumed to occur exogenously while households might have different perceptions and experiences towards the exogenously existed drought and they decide whether to use child labor or not accordingly.

All of the three-round panel data had shock variables which represent as to whether a household experiences the range of adverse shocks which consists of drought and other agricultural shocks due to pests, natural disasters, death or illness in the family and unemployment. I have chosen the shock variable that exogenously exists to the population and based on the response from the majority of the households about the types of shocks experienced at the year of the survey. A drought was reported to be a number one shock experienced by the majority of the households in the study area (see table 8). The coefficient of interest in the Pooled OLS panel data analysis is \(\alpha_1\) (an estimated coefficient on drought dummy).
The relationship between drought and hours of work by the child is likely to be affected by several observable time-invariant and time-variant control variables other un-observable factors.

The data for some of the variables that are thought to have an association with hours of work by a child, for example, the ability of the child and the risk-taking behavior of the parents are not included in the Young Lives data set. If one or more of these variables were determinants of the hours of work of a child and correlated with drought, the omitted variable bias would be a big concern. Estimates that do not control for unobserved heterogeneity are biased. Therefore, due to the suspect of sample selection problem which is one example of the existence of an omitted variable and the missing data for the potential unobservable control variables, the Pooled OLS panel estimation model is not chosen for this study.

However, the two-way error component panel data estimation models, especially fixed effect panel data model, can help to reduce this problem by controlling some omitted variables even if they are unobserved.

3.5.1 Two way error component panel regression model
The basic log-linear panel data model can be rewritten in a way that accounts a decomposed disturbance terms.

\[
\log \text{Hours}_{it} = \alpha_0 + \alpha_1 \text{drought}_{it} + X'_{it}\beta + \varepsilon_{it} \tag{2}
\]

\[
\varepsilon_{it} = Z_{it}\eta_i + Z_{it}\delta_t + \upsilon_{it}
\]

The main variables in equation (2) are:-

- **logHours**<sub>it</sub>, a continuous variable which measures the log of average hours of work per day by a child i in the survey year t.
- **drought**<sub>it</sub>, a variable of interest, is a binary variable which captures whether the individual i perceives a drought shock in year t. A drought is expected to exist exogenously to every household at a given period or survey round. However, its existence might be perceived differently by different individuals. The differences in perception of drought, due to many differences between households, influence the individual’s decision to use child labor and are expected to bring a variation in the average hours of work accordingly. Hence, the
assumption employed in this model is that the causality only runs from drought to hours of work by a child and focuses on the estimated coefficient on $drought_{it}$.

- $X_{it}$, which include the vector of household and individual control variables, is included to deal with the problem of an omitted variable bias that may arise if the households’/individual’s time variant variable/s which correlates with the hours of work is omitted even if I controlled the individual and time fixed effects.

- $\eta_i$, represents the time-invariant unobservable characteristics of the individual like gender and the area of residence (rural vs. urban) which captures the individual fixed effects and mitigates the omitted variable bias.

- $\delta_t$ is the time fixed effect that accounts for the unobservable time-specific effect which is not included in the regression. It accounts, for example, the child labor rules and regulation of the country which are typical for all households but varying over time. One of the survey rounds has to be considered as a base year because an intercept term is already included in this panel data model. Otherwise, it creates a dummy variable trap, and the main intercept term has to be excluded if all time dummies are required to appear in the regression result.

- $\epsilon_{it}$, in the first line of equation (2), it represents the overall disturbance term of the model. However, in the second line of equation (2), the disturbance term is decomposed into: unobservable individual effect ($\eta_i$) and unobservable time effects ($\delta_t$). The terms $Z_{\eta} + Z_{\delta}$ are matrices of all the dummy variables that might have an effect on hours of work and are included in the panel regression model.

- The coefficient $\alpha_0$ represents a constant term (intercept) in the regression model while $\alpha_1$ measures the effect of perceiving a drought shock by the individual on the average hours of work holding other controls constant.

Two main panel data models are employed for this estimation: fixed-effects and random-effects models.

### 3.5.1.1. Fixed effect model

A Fixed effect is the most common panel data estimation technique which controls for time-invariant omitted variables in the panel data. Applying fixed effect panel data estimation helps to deal with the unobservable factors by taking out the part that is constant over time. The variation in the household or child specific time-invariant effects comes from omitted variables and varies
across households and/or the child but not over time. Therefore, \( n \) different intercepts will be calculated, one for each entity when the Fixed effect panel data estimation is employed. Hence, the intercept in the fixed effect panel estimation represents the effect of being in entity \( i \).

The main assumption for fixed effect estimation is that the individual specific effects are treated as parameters to be estimated, i.e., \( \eta_i \) and \( \delta_t \) are to be estimated while \( v_{it} \sim \text{IID} (0, \sigma_v^2) \), and \( X_{it} \) are independent of \( v_{it} \) for all \( i \) and \( t \). The estimates of the coefficients from within transformation are more consistent in the fixed effect estimator than the OLS estimator. However, the drop of time-invariant in the fixed effect estimation affects the efficiency of the estimate due to the loss of degrees of freedom, i.e., \( N (T-1) \).

Hence, applying individual fixed effect largely copes with the empirical challenge to disentangle the link between the individual’s complex (time-invariant) conditions and the decisions to use child labor. Shocks such as drought can be seen as more exogenous to the child than shocks related to illness or unemployment (De Janvry et al. 2006). Hence, drought was chosen to be included as an exogenous explanatory variable in this study. Shocks alter the decision of a household on the use of child time. Adverse shocks like drought increase the probability that a child will work (Guarcello et al., 2010).

A drought is an exogenous variable in the population which reduces the endogeneity problem. However, it seems that there is a sample selection problem since hours of work by a child might only be observed after the household decides to use child labor. Hence, there will be an omitted variable bias if the residuals of the hours of work and use of child labor decisions correlate (if the correlation is different from zero). If the omitted unobservable individual heterogeneity for the decision to use child labor (or child work) is not random and the sample is non-random, then OLS cannot be the best estimation model. Besides to this, the data for the unobservable individual heterogeneity factors: for example, the ability of a child and attitude of the household towards child labor and risk-taking are not available in the dataset. Therefore, fixed effect panel estimation model is chosen because it controls for those potential un-observable individual heterogeneity.

For this reason, fixed effect panel estimation is employed in this study to eliminate the time-invariant unobserved heterogeneity between individuals. Within variation is taken into account...
to identify the model. The individual fixed effect takes into account that the main independent
variable, i.e., perception towards drought, varies at the child level (within variation). Beegle et al.
(2006) argue that using individual fixed effect also means to focus on the idiosyncratic
component of the shock.

It should be noted that since the sample contains one observation per household and the use of
child labor is often decided by the parent, child (individual) fixed effects also incorporate family
fixed effects in this study.

Some essential time-variant individual and household characteristics are included in the
regression to reduce the problem of omitted variable bias. The time variant characteristics that
are thought to be correlated with the hours of work by the child are the age of the child, age
square of a child, household size, wealth index of the family, land ownership and access to
credit. For example, a wealthy family or a family who has access to credit can have the ability to
cope the drought shock which leads to a reduction in hours of work by a child. A child from the
low-income family might be forced to work to support its family or supplement the household
income, which is consistent with the luxury axiom of (Basu and Van, 1998).

A child might also get more responsibilities in helping its siblings as its age increases. The older
the head of the family the lesser will be the contribution to the family and the more workload
might rest on the shoulder of the child which leads to more working hours by the child. On top of
this, some of the variables like the land of the household might not be cultivated at the drought
season which leads to a reduction in child labor while the land needs more labor at the monsoon
so that the demand for child labor increases.

The unobservable time-invariant characteristics of the child and the household that might affect
their decision to work (or use child labor) might create an omitted variable bias problem as well.
If these un-observables are not included in the regression due to, for example, lack of data, then
using OLS will no longer be an efficient and consistent estimator. The fixed effect, however, can
give us a better estimate because it fixes the time-invariant un-observables that might have
correlated with the variables included in the regression.

Several empirical and econometric pieces of literature also advise the use of fixed effect to deal
with omitted variable bias problems (Clark and Linzer (2015) and Riegg (2008)). A clustering of
the standard errors at an individual level and log transformation of the dependent variable were also performed to account for a serial correlation of error terms and heteroscedasticity problem.

3.5.1.2. Random effect model

Random effect panel estimation works by transferring the unobserved child effects to the error term, and it does not estimate the fixed effect for each child.

In this model, the child-specific effects are treated as outcomes of a random variable following a known distribution i.e. $\eta_i \sim \text{IID}(0, \sigma^2_{\eta})$, $\delta_t \sim \text{IID}(0, \sigma^2_{\delta})$ and $v_{it} \sim \text{IID}(0, \sigma^2_v)$ are independent of each other and drought$_i$ is independent of $\eta_i$, $\delta_t$, $v_{it}$ for all $i$ and $t$. Hence, it is assumed that they are I.I.D., and draw from a normal distribution.

Therefore, the random effect estimation model does not lose any degree of freedom as the individual time-invariant unobservable ($\eta_i$) and time specific effect ($\delta_t$) are random and they are independent of $v_{it}$.

The parameters in the random effects model are estimated under the assumption of zero correlation between the household-specific effect and the error term plus the other explanatory variables. If this strong assumption is not satisfied, then it can entail a risk of obtaining inconsistent estimates. The problem with using random effect panel estimation model for this study is that the error terms (i.e., residuals from the selection to child labor decision and the hours of work outcome variable) might not be independent. Hence, the correlation of this two error terms and the absence of data to introduce controls that may capture the individual heterogeneity makes the random effect panel estimation model not suitable for this study. Conducting a statistical test is also good to check whether the omitted unobservable individual heterogeneity are random or not and then choosing the best model that estimates the best under these circumstances.

Therefore, to choose between random effect and fixed effect panel estimation models a Hausman statistical test is accomplished. The statistical test result shows that fixed effect panel estimation model is suitable for this data set (see Appendix I for the Hausman test). Consequently, using the Hausman statistical test result, the theoretical justifications and similar previous empirical
research evidences in dealing with possible omitted variable bias, a fixed effect model is found to be the best panel estimation model for this study.

**3.6. Choice of control variables**

The final major modeling choice in this study is a choice of control variables to deal with time variant observable omitted variable bias. The choice of explanatory variables that are thought to have an association, with the number of hours of work by a child (child labor supply) is conducted based on the pieces of evidence of previous empirical findings and child labor theories.

The selected controls are:

1) **Age of the child:** The individual characteristic that is likely to be an important determinant of hours of work is a child's age. Some empirical evidence suggests that the relationship is positive and quadratic, usually peaking in early adulthood. The age profile of child time use is thus potentially very complex involving the continued confrontation of the costs and benefits of alternative time uses as a child grows older.

2) **Wealth index:** Household wealth is the most studied topic as much of the policy debate concerns the necessity of child labor for poor households and the appropriateness of using income-oriented policies. The highest the wealth index reflects (household located in the highest income quintile) how rich the families of the child are. This could be reflected in a reduced hours of work by a child. As the level of consumption falls below subsistence levels, child labor might be highly demanded especially by the poor families (Basu and Van, 1998) and (Ray, 2000).

3) **Access to credit:** It is believed that the household’s income needed from the child’s work to help its siblings and parents can be compensated by borrowing from the bank or other non-formal credit institutions. Child labor is expected to increase with families who have borrowing constraints and less access to formal credit markets. Child labor and access to credit, by minimizing the underinvestment on human capital, have a negative relationship (Baland and Robinson (2000), Guarcello et.al, (2010), and Dehejia and Gatti (2002)). This indicates that lack of access to credit prevents a household especially a poor household from relying on outside markets to reduce the impact of drought. However, households with an access to credit can
reduce the effect of drought shock on their daily lives by taking credit while those without credit access use more child labor as a drought coping mechanism.

4) Household size:- It may affect hours of work by a child in a many ways. The marginal productivity of labor in the household production is thought to go down if the household’s production assets are fixed in size like land and fixed in number like the livestock. Hence, the demand to use child labor in the household production will go down in large size households with fixed assets. But there might be cases that as the size of the family gets larger, more and more effort could be needed from a child to help the household expenses and/or smooth the family consumption. Family size is thought to be positively related to child labor. It is clear that if a family size increases then the income per capita will decrease which leads to a rise in the dependency ratio and an increase in the use of child labor (Buchmann, 2000).

5) Age of the household head:- The help needed from a child is thought to increase as the age of the household head increases. They might put all the workload on the child. Hence the age of the household head will have a positive association with hours of work by the child. The demand for child labor might even be more in the drought seasons where the numbers of dependents are expected to increase.

6) Land ownership:- I thought that land ownership is expected to vary based on the time that the household gets the land or they lose it due to renting or sale of it. It is likely that it changes over time for the reasons that families might exchange land over the duration of the survey. Hence, land ownership cannot be wiped out by a fixed effect and it is a good option to introduce it to the regression for checking an omitted variable bias. Andvig et.al (1999) finds higher child labor in farming households who have a land vice versa.

7) Other time-invariant characteristics that could bring a variation if a pooled OLS or Random effect were the choices are in the rural or urban residence of the child. Parents living in rural areas are dependent on farmlands and livestock herding than the urban counterparts who rely on wage income and business operations. Hence, the residence of the households is also expected to have a significant impact on child labor supply. Besides to this, the availability and access to infrastructure and other support services are different to a more considerable extent in the rural versus urban population.
Therefore, their residence and the level of access to support services from governments, non-governmental organizations and institutions are expected to have a significant effect on the child labor supply. Hence, child labor supply is supposed to be high in the rural area than the urban counterparts. Therefore, the degree of urbanization of community/districts where the child lives may reduce child labor. Five district dummies are included and tested for a district (Region) fixed effects.

The existing gender biased jobs might also bring a variation on child labor (Ersado, 2005). Male child has been working more hours than female child globally (UNICEF, 2012). However, this might not be consistent in the drought seasons and in countries where jobs are categorized as gender specific.

For example, in Ethiopia, where this study is conducted, boys are supposed to work outside of the home activities while girls most of the time are required to work at home. In most developing and rural societies boys are expected to spend their labor time on helping parents at the farmlands and cattle herding while girls spend their time looking after their younger kids, fetching water and making food for the family.

Hence, a gender bias in the household allocation of schooling time and costs, boys may be more likely to attend school while girls are expected to work. Consequently, it may result in a reduced child labor for boys while increased labor participation for girls. Therefore, at a drought season boys might work less because the farm activities are less while the workload for girls might still be the same as long as the work inside the home is meant for girls.

However, these unobservable time-invariant characteristics are fixed at the individual level because of the use of fixed effect panel estimation.
Chapter 4: Results and Discussion

This section deals with regression results, analysis, and discussion. The log of hours of work represents the average hours spent on any task per day: market work, farm work cooking, fetching water, and collecting woods, selling in the family business, caring young child, herding cattle, and other domestic chores. The main estimation model used in this study is fixed effect model. But the results of the Pooled OLS and Random effect estimations are also presented in the same tables just for comparison purpose.

Fig 1: Hours of work in drought vs. out of drought season.

Source: Author’s sketched graph from UK data service, Young Lives data

Figure 1 shows the difference in average hours of work regarding the percentage of a child working when the household perceive a drought shock. The graph shows that most of the children have worked more hours in the drought season while they work fewer hours in the absence of drought. Most children worked an average of 4-6 hours in the drought season while it was 2-3 hours in the absence of drought. This descriptive statistical result is consistent with the luxury axiom of the child labor and human capital theories of (Basu and Van, 1998) and (Baland and Robinson, 2000).
4.1. Regression results and discussion

A fixed effect panel regression with one independent variable, i.e., household's perception towards drought shock was conducted before I tend to include other potential controls to deal with omitted variable bias. Time fixed effect (time dummy) is also introduced to see whether there are unobserved variables which vary over time but constant across individuals while they are not included in the regression. The definitions of all the variables are included in table 9.

Table 9: Definition of the main variables used in the regression

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Value label</th>
<th>variable label</th>
</tr>
</thead>
<tbody>
<tr>
<td>loghours</td>
<td>continuous</td>
<td>Log of average Hours of work per day</td>
</tr>
<tr>
<td>Drought</td>
<td>Dummy for Yes=1 ; 0 otherwise</td>
<td>A household self reported drought shock</td>
</tr>
<tr>
<td>Age</td>
<td>Continuous variable</td>
<td>Age of a child in years</td>
</tr>
<tr>
<td>age2</td>
<td>Continuous variable</td>
<td>age squared of a child in years</td>
</tr>
<tr>
<td>hhsize</td>
<td>Continuous variable</td>
<td>Household Size in number</td>
</tr>
<tr>
<td>AGEHH</td>
<td>Continuous variable</td>
<td>Age of household Head in number</td>
</tr>
<tr>
<td>wi</td>
<td>Continuous variable</td>
<td>wealth index in number</td>
</tr>
<tr>
<td>Credit</td>
<td>Dummy for Yes=1 ; 0 otherwise</td>
<td>HH access to credit/finance</td>
</tr>
<tr>
<td>OWNLAND</td>
<td>Dummy for Yes=1 ; 0 otherwise</td>
<td>household owns a land currently</td>
</tr>
<tr>
<td>Male</td>
<td>Dummy for Yes=1 ; 0 otherwise</td>
<td>sex of a child</td>
</tr>
<tr>
<td>Rural</td>
<td>Dummy for Yes=1 ; 0 otherwise</td>
<td>child lives in rural area</td>
</tr>
<tr>
<td>Year</td>
<td>Categorical variable for 2006=1, 2009=2 and 2013=3</td>
<td>Year of survey</td>
</tr>
</tbody>
</table>

Source: Author’s selected variables from UK data service, Young Lives data

The analysis starts with the regression of log hours of work on the perceived drought shock by the household. However, it is difficult to take the estimated coefficient (see table 10) on drought to be a causal effect without justifying for a reverse causality and checking for possible omitted variable bias. Fixed effect panel estimation controls the unobservable time-invariant factors, but it cannot control the omitted variable bias that might come from the potential time-variant variables which are not included in the regression. Some theoretically and empirically
recommended essential variables are included in the regression to reduce the time-variant omitted variable problem, (see table 12).

Discussing the reverse causality (or endogeneity) problem is also important before starting the interpretation and discussion. The chosen variable of interest from the independent variables side is drought. A drought exists exogenously to the population. To my knowledge, no theoretical and empirical literature explains the effect of hours of work by a child on the existence of drought. Therefore, there is less likely for the reverse causality (or endogeneity) problem to exist.

However, a variation in the perception of drought shock is observed among children within a year and within a child across years. The between variations might come due to several unobservable heterogeneities of the individuals in evaluating the adverse effect of drought shock and their coping ability in addition to the observable differences between individuals like age and wealth level of the households. The within variation about drought and hours of work might be a result of the time-varying un-observables but constant between individuals like the introduction of drought resilient technologies by the government, seasonal weather variations like good rain year and the observable time-varying factors that are constant across individuals like the GDP per-capita growth and development.

Therefore, potential time-variant variables are included to reduce omitted variable bias and to see the within variation in working hours that is thought to come from the variation in perception towards drought shock. However, these individual factors that bring a within variation are controlled by the fixed effect. Consequently, clustering of error terms at an individual level is performed to reduce serial correlation of errors and heteroscedasticity problem. In addition to this, a log transformation of the dependent variable was done to prevent from outliers and to maintain the normality of the continuous dependent variable.

Hausman test is conducted to choose the most appropriate model from the fixed effect and the random effect estimation models (see the result in appendix I). The null hypothesis of the Hausman statistical test states that the two estimation methods are both suitable and yield the same coefficients. Nonetheless, the null hypothesis which claims that there is no difference between the two estimators is rejected at a 1% significance level in favors of the alternative hypothesis that the use of fixed effect panel data estimator is suitable. The comparison of fixed
effect and random effect estimation models using the Hausman test is conducted before clustering the standard error at an individual level.

From the very reason that both random effect and OLS rely on the same assumptions for consistency, rejecting random effect by the Hausman test is likely to reject Pooled OLS too. Therefore, fixed effect estimation is the best choice that gives a consistent estimate in this study. The estimated coefficients from the fixed effect panel data model are also the primary focus of the analysis and discussion in this study.

A Breusch-pagan Lagrange multiplier test is also conducted to choose a suitable model between Pooled OLS and Random effect. The statistical test result shows that the null hypothesis which states that there is no significant difference between units or the variance between entities is zero (or no panel effect) cannot be rejected. Hence, the failure to reject the null hypothesis indicates that Random effect is not appropriate.

Table 10: comparing the effect of drought on child labor using the three panel estimation models without other controls.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pooled OLS</th>
<th>Fixed Effect</th>
<th>Random Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drought</td>
<td>.38***</td>
<td>.41***</td>
<td>.38***</td>
</tr>
<tr>
<td></td>
<td>(.028)</td>
<td>(.04)</td>
<td>(.028)</td>
</tr>
<tr>
<td>_cons</td>
<td>1.20</td>
<td>1.19</td>
<td>1.20</td>
</tr>
<tr>
<td></td>
<td>(.016)</td>
<td>(.010)</td>
<td>(.016)</td>
</tr>
<tr>
<td>observations</td>
<td>2733</td>
<td>2733</td>
<td>2733</td>
</tr>
<tr>
<td>R²</td>
<td>.0532</td>
<td>.0532</td>
<td>.0532</td>
</tr>
</tbody>
</table>

Note that standard errors are clustered at the individual level and reported in parenthesis. ***(1%), **(5%), *(10%) significance level (two-tailed) respectively.

Source: Regression results based on the UK-data service, Young Lives dataset.

Table 10 gives a regression result without other controls. In this regression, data from a three-round panel (2006-2013) and a full sample of 981 children are used. The sampled children were the same in three of the survey rounds. The $a1$ is estimated to be positive and significant at the
1% significance level in three of the estimation models. The results from the Pooled OLS and random effect models are also included in the table (10) while it is only for comparison purpose. Otherwise, the estimated coefficients reported and used for an analysis and discussions in the rest of the thesis are just taken from the fixed effect model.

However, it is difficult to conclude that the estimated $\alpha_1$ coefficient is causal. Therefore, a regression with additional control variables is the best strategy to deal with the possibility of omitted variable bias. I have conducted fixed effect panel estimation for the same sample of children by including other possible controls that are thought to be correlated with the hours of work by the child. The results are given in table 12.

**Table 11: A fixed effect regression with time dummies**

<table>
<thead>
<tr>
<th></th>
<th>LogHW</th>
<th>Fixed effect without time fixed effect</th>
<th>Fixed effect with time fixed effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drought</td>
<td>.41***(.04)</td>
<td>.33***(.04)</td>
<td></td>
</tr>
<tr>
<td>2009</td>
<td>-.40***(.028)</td>
<td>.36***(.029)</td>
<td></td>
</tr>
<tr>
<td>2013</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>_cons</td>
<td>1.19(.01)</td>
<td>1.25(.021)</td>
<td></td>
</tr>
</tbody>
</table>

Note that standard errors are clustered at the individual level and reported in parenthesis. ***(1%), **(5%), *(10%) significance level (two-tailed) respectively.

Source: Regression results based on the UK-data service, Young Lives dataset.

Table 11 shows the effect of time-varying un-observables. This regression is conducted to see if there are un-observables that might be the same for every child but varying over time. For example, the government might have imposed a strict regulation towards child labor or a compulsory free primary education for all children and weather conditions might be changed between survey rounds so that the observed hours of work by the child reduces or increases across time but not across individuals.
It would be easy to do by introducing a potential variable that represents this policy and weather changes if the data for these variables are recorded. However, there is no data related to these policy changes in the Young Lives dataset.

Therefore, a time fixed effect regression was conducted by introducing time dummies which are expected to capture those time-varying un-observables. The test shows that there are significant potential time-varying un-observables and adding a time dummy to capture that effect is advisable. The statistical test result reads:

\begin{align*}
(1) & \quad 2009.\text{Year} = 0 \\
(2) & \quad 2013.\text{Year} = 0 \\
& \quad F(2, 981) = 344.06 \\
& \quad \text{Prob} > F = 0.0000.
\end{align*}

Therefore, the null hypothesis which states that the coefficients for all years are jointly equal to zero is rejected at a 1% significance level. It indicates that time fixed effects (or introducing time dummy to the regression) are important in this panel data model.

The importance of time dummies is also tested with the pooled OLS and random effect models. The null is rejected at 1% significance level which indicates that it is also important if we add a time dummy in each of the regression models too. The year 2006 is considered to be the base year in this regression. Hence, only the coefficients for 2009 and 2013 survey rounds are displayed in the regression.

The estimated $\alpha_1$ on drought has decreased significantly after I include the time dummy. This might be due to the case that the unobservable time-varying variables (for example, the government policy towards combating child labor) were negatively related to hours of work (or use of child labor).

A fixed effect regression of hours of work on drought with the district (Region) fixed effect is also conducted, but it shows no significant change in the estimated coefficient of drought. The included district(Region) dummies which capture the district fixed effect also show no
significant difference in hours of work by the child except Tigray region which shows a significant and higher hours of work than the base district, Addis Ababa city (see Appendix III).

Table 12: A Fixed effect regression results with other controls

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pooled OLS</th>
<th>Fixed Effect</th>
<th>Random Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drought</td>
<td>.24***(.033)</td>
<td>.29***(.04)</td>
<td>.24***(.03)</td>
</tr>
<tr>
<td>Age</td>
<td>.61**(.29)</td>
<td>.41**(.20)</td>
<td>.61**(.29)</td>
</tr>
<tr>
<td>age2</td>
<td>-.02**(01)</td>
<td>-.01*(.006)</td>
<td>-.02**(01)</td>
</tr>
<tr>
<td>hhsiz</td>
<td>-.005(.006)</td>
<td>-.019(.012)</td>
<td>-.005(.006)</td>
</tr>
<tr>
<td>AGEHH</td>
<td>.0006(.001)</td>
<td>.0004(.001)</td>
<td>.0006(.001)</td>
</tr>
<tr>
<td>wi</td>
<td>-.58***(.11)</td>
<td>.10(.18)</td>
<td>-.58***(.11)</td>
</tr>
<tr>
<td>Credit</td>
<td>-.012***(.003)</td>
<td>-.02***(.004)</td>
<td>-.01***(.003)</td>
</tr>
<tr>
<td>OWNLAND</td>
<td>.19***(.05)</td>
<td>.13(.05)</td>
<td>.19***(.05)</td>
</tr>
<tr>
<td>Male</td>
<td>-.09***(.03)</td>
<td>0</td>
<td>-.09***(.03)</td>
</tr>
<tr>
<td>Rural</td>
<td>.10**(.04)</td>
<td>0</td>
<td>.10**(.039)</td>
</tr>
<tr>
<td>Year</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2009</td>
<td>-.36***(.11)</td>
<td>-.68***(.16)</td>
<td>-.36***(.11)</td>
</tr>
<tr>
<td>2013</td>
<td>.62**(.32)</td>
<td>-.008(.27)</td>
<td>.62**(.32)</td>
</tr>
<tr>
<td>_cons</td>
<td>-2.95(2.03)</td>
<td>-2.03(1.57)</td>
<td>-2.95(2.03)</td>
</tr>
<tr>
<td>Observations</td>
<td>2028</td>
<td>2028</td>
<td>2028</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.2338</td>
<td>.2422</td>
<td>.2338</td>
</tr>
</tbody>
</table>

Note that standard errors are clustered at the individual level and reported in parenthesis. *** (1%), ** (5%), * (10%) significance level (two-tailed) respectively. Results are estimated based on the UK-data service, Young Lives dataset.

Column (3) of table 12 shows the fixed effect estimate of a log of hours of work on drought experience. The estimate of $a_1$ is found to be positive and significant at the 1% significance level. However, the estimate of $a_1$ decreases substantially after a candidate control variables including the time dummy was added.
This indicates that there would be an omitted variable bias if these variables were not included in the regression. The decrease in the estimated $\alpha_1$ could be due to some of the controls that associate with the child labor negatively and dominate the influence of other variables that positively relate to it.

In addition to the potential child and household control variables, a time fixed effect (time dummy) is also added into the regression to see if there is a difference in the intercepts between individuals and across time. Compared to the 2006 estimated time intercept, it shows that there is a significant difference on the intercepts at 1% and 5% significance levels for the 2009 and 2013 time dummies respectively.

The result indicates that there is a variation in the intercept between children and across time while the estimated slope coefficients are the same. For example, the 2009 year dummy shows that the intercept term is less than the 2006 intercept term which will affect the predicted value of the children when the time intercepts are added or subtracted to a given actual data values of the child.

The variation in hours of work might also be explained due to some unobserved factors that vary over time but not across individuals like the child labor and implementing drought resilient policies and strategies of the country.

Therefore, ceteris paribus, the estimated $\alpha_1$ shows that the individual's perception towards drought shock has a positive relationship with hours of work. Consequently, the higher the individual weights the effect of drought shock on his/her life the higher will be the hours of work. The coefficient on the fixed effect estimation can be interpreted as; the average hours of work by a child increases by 29% when the household perceives there is drought shock.

The result indicates that a household demand more help from the child to sustain their family life in the drought season. Basu and Van, (1998) argue that poverty is the main reason for a child labor and child work is demanded by the respective household when their consumption level drops to below subsistence level due to, for example, a drought’s impact on some loss of income opportunities. Hence, it can be observed from the result that luxury axiom dominates substitution axiom when households perceive a drought.
This result is consistent with the empirical finding by Guarcello et al. (2010) who find that child labor increases in response to drought and other negative shocks. It is also consistent with some previous empirical findings on the impact of adverse shocks, and they find a significant increase in child labor (Beegle et al., 2003). This result makes sense since least developed countries are mostly dependent on agriculture. Agriculturalists and poor households are likely to develop a negative perception of drought shock. These observable differences could be the reasons out of the many unobservable differences which brought a variation on hours of work between children while drought exists exogenously as a common shock for all.

It is also expected to see a difference in perception about drought and their choice of drought coping strategies. For example, some households might have assets to sell and others might get a credit while others don’t have these all but only to use child labor as insurance to drought shock.
Chapter 5: Conclusion and Recommendation

5.1. Conclusion

Encouraging works and initiatives are being taken both in the literature and by both the industrialized and developing country governments related to the inefficiency and illegality of child labor. A lot of discussions have been made related to the supply and demand side factors that abuse the right of a child to be safe and protected from hazardous and physically demanding works.

The general objective of this study is to estimate the causal effect of household’s perception towards drought shock on the use of child labor. Secondary data were accessed from the UK data service, Young Lives program which they collected it in a three household survey rounds from Ethiopia. A child fixed effect panel estimation model was used. As the household most often decides the decision whether to use child labor or not primarily by the household head, a household fixed effect is thought to incorporate the individual (child) fixed effect as well. Therefore, I had interchangeably used the household or individual or both when I wanted to explain unobservable time-invariant characteristics of the child using fixed effects in the thesis.

The unobservable time-invariant characteristics of the household which is thought to affect the decision of the household on using child labor are fixed by the fixed effect panel data estimation model. First, the causal effect of perception of drought on hours of work by a child was conducted, and the estimated coefficient is positive and significant at a 1% significance level. However, it is difficult to consider this coefficient as a causal effect.

For this reason, potential control variables were added to deal with omitted variable bias. The estimated coefficient α1 shows a substantial decrease while it still has a positive relationship at a 1% significance level. The reduction in the coefficient indicates that there would be an omitted variable bias if these controls were left out. A time dummy (time fixed effect) was also added to see if there is a significant difference in the intercepts between individuals and across survey rounds that comes from factors that vary over time but constant between the children like some child labor policy changes over the years. The time fixed effect shows that including a time dummy or (time fixed effect) is important and shows a difference in the intercepts while keeping the estimated slopes the same.
The main finding shows that perception of drought by households has a varying effect on the use of child labor. And this is reflected by the higher number of hours worked per day by a child in different rounds. Keeping other things constant, it is estimated that a child works 29% more hours if a household perceived the adverse effect of drought shock than if they do not perceive it.

Other time variant control variables were included to deal with omitted variable bias. Some of them were found to be significantly associated with average hours of work by a child: child age(+), age square of the child(-) and access to credit(-) which indicates that excluding the significant control variables could result in an omitted variable bias.

5.2. Recommendation

Hours of work by a child are associated strongly with the perception of drought shock by the household. If households lack other coping mechanisms (for example, if they are borrowing constrained and they don’t have an asset to be sold), it seems that their next survival strategy is to use a child labor. Therefore, this indicates that households, especially those who are borrowing constrained and mostly affected by the natural disaster, should be supported by governments and global institutions which are working on eradication of child labor and protecting child rights.

After controlling the access to credit in the fixed effect estimation, the finding shows that there is a significant and negative relationship with a log of average hours of work. The result indicates that parents might use credit as a coping mechanism towards shocks if they can take and access credit while using no or less child labor. In most countries, poverty alleviation is a long-term objective. Hence, short-term actions aimed at reducing drought shock vulnerability for poor households might also have beneficial effects on child labor reduction.

It is also recommended that the government should design a drought-resilient agricultural production and business activity for the society because the result indicates that child labor has shown a significant increase in the perceived drought existing season. Delivering an effective training on child labor and its consequences, encouraging the households to adopt drought resilient production systems and promoting jobs which are less likely to be affected by drought are recommended to combat child labor among other government policy actions.
References:


41. UNICEF (United Nations Children’s Fund), 2012. UNICEF Annual Report 2012 for Ethiopia, ESARO. It available also at the following link :-
42. UNICEF (United Nations Children’s Fund), 2016. Child labour-UNICEF Data. Also available at the web page :-
Appendices

Appendix I: Hausman test

. hauser fe re

<table>
<thead>
<tr>
<th>(b)</th>
<th>(B)</th>
<th>(b-B)</th>
<th>sqrt(diag(V_b-V_B))</th>
<th>s.e.</th>
</tr>
</thead>
<tbody>
<tr>
<td>fe</td>
<td>re</td>
<td>Difference</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drought</td>
<td>.09056</td>
<td>.246032</td>
<td>.052020</td>
<td>.0061216</td>
</tr>
<tr>
<td>Age</td>
<td>.0110185</td>
<td>.0219899</td>
<td>.0101804</td>
<td>.</td>
</tr>
<tr>
<td>age2</td>
<td>.0194776</td>
<td>.0052281</td>
<td>.0142495</td>
<td>.0081534</td>
</tr>
<tr>
<td>AGEEH</td>
<td>.0004259</td>
<td>.0006327</td>
<td>-.0002067</td>
<td>.0000453</td>
</tr>
<tr>
<td>wi</td>
<td>.1019303</td>
<td>-.5840169</td>
<td>.6859202</td>
<td>.1160914</td>
</tr>
<tr>
<td>Credit</td>
<td>-.0196668</td>
<td>-.0026237</td>
<td>-.0070341</td>
<td>.0026465</td>
</tr>
<tr>
<td>OWN LAND</td>
<td>.1333703</td>
<td>.1955447</td>
<td>-.0621744</td>
<td>.0253978</td>
</tr>
<tr>
<td>2009 Year</td>
<td>-.683086</td>
<td>-.3694469</td>
<td>-.3164111</td>
<td>.1285333</td>
</tr>
<tr>
<td>2013 Year</td>
<td>-.0088446</td>
<td>-.6202409</td>
<td>-.6290855</td>
<td>.0789004</td>
</tr>
</tbody>
</table>

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ho, efficient under Ha; obtained from xtreg

Test: Ho: difference in coefficients not systematic

\[
\chi^2(10) = (b-B)'[V_{b-B}]^{-1}(b-B)
\]

\[
\text{Prob}>\chi^2 = 0.0000
\]

(Y_b-Y_B is not positive definite)

Appendix II. Breusch and pagan test for random effect

Breusch and Pagan Lagrangian multiplier test for random effects

\[
\text{Hourswork}[\text{CHILDID},t] = X_b + u[\text{CHILDID}] + e[\text{CHILDID},t]
\]

Estimated results:

<table>
<thead>
<tr>
<th>Var</th>
<th>sd = sqrt(Var)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hourswork</td>
<td>8.500125</td>
</tr>
<tr>
<td>e</td>
<td>8.508842</td>
</tr>
<tr>
<td>u</td>
<td>0</td>
</tr>
</tbody>
</table>

Test: \(\text{Var}(u) = 0\)

\[
\text{chibar2}(01) = 0.00
\]

\[
\text{Prob} > \text{chibar2} = 1.0000
\]
Appendix III: A test for district fixed effect

Fixed-effects (within) regression  
Group variable: CHILIDID  
Number of obs = 2732  
Number of groups = 982  

R-sq: within = 0.0477  
between = 0.0612  
overall = 0.0560  

Obs per group: min = 1  
avg = 2.8  
max = 3  

\( F(981, 2720) = \) .  
Prob > F = .  

(Std. Err. adjusted for 982 clusters in CHILIDID)

| logHM | Coef.  | Std. Err. | t     | P>|t|  | 95% Conf. Interval |
|-------|--------|-----------|-------|------|-------------------|
| Drought | .4129615 | .0430818 | 9.58  | 0.000 | .3289184 .4974046 |
| District | 2 | .028571 | .0215409 | 1.33 | 0.185 | -.0137003 .0708426 |
| District | 3 | .7199938 | .5607855 | 1.28 | 0.199 | -.3804833 1.820471 |
| District | 4 | -.3945642 | .4909811 | -0.79 | 0.429 | -.1373757 .5846289 |
| District | 5 | .83329 | .0215409 | 38.68 | 0.000 | .7910185 .8755616 |
| _cons | .9615351 | .2286006 | 4.21  | 0.000 | .5129326 1.410139 |

sigma_u | .5918815  
sigma_e | .6960571  
rho | .41963993  
\( \text{(fraction of variance due to u_i)} \)