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Child Labor as a Coping Mechanism

Children's Time Use Responses to Community and Individual Shocks

by

Theresa Pieper - th4747pi-s@student.lu.se

Abstract

This thesis explores the impact of community and individual shocks on children's time use and aims to determine if and under what conditions households use child labor as a response to shocks. For this purpose, four survey rounds of a panel of Ethiopian children aged 5 to 15 are analysed. To address endogeneity problems and to overcome issues related to the data acquisition process, both a fixed effects and a matched difference-in-difference model are applied. The results show that children significantly increase their hours of work when they experience either of the two shocks, while this is not the case for hours spent on chores. Factors like age, the socio-economic and the rural/urban status lead to heterogeneous results. However, no gendered effects are found. This thesis provides important policy recommendations concerning the importance and the nature of formal coping strategies that should be provided for households to be able to deal with shocks without resorting to child labor.

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Declaration

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Contents

List of Figures

List of Tables

1

Introduction

Shocks and uncertainties are defining factors that determine household behavior in development countries (Banerjee and Duflo, 2007). Poor people are often victims of a range of risks while lacking formal strategies to cope with shocks. Instead, a variety of informal strategies exist (Pradhan and Mukherjee, 2018). One such strategy is the employment of children to increase the household labor supply. This thesis examines the nexus between community and individual shocks and child labor in Ethiopia.

Child labor is a complex phenomenon which is prevalent in many developing economies and appears in various forms. Following the definition by ILO and UNICEF (2021), child labor includes work performed by children in the formal and informal economy, inside and outside family settings and for pay or profit as well as domestic work outside the child's own household for an employer (paid or unpaid). Unpaid household chores provided for the own household are excluded (ILO and UNICEF, 2021). 160 million children (63 million girls, 97 million boys) were child laborers in 2020, making up 10% of the worldwide child population (ILO and UNICEF, 2021). Of those, 79 million children were working in hazardous conditions. The prevalence of child labor increases with age. In 2016, 25% of children aged 15 to 17 years old worldwide were in employment while only 11% of the 5- to 14-year-olds were in employment (ILO, 2016). The world region with the highest child labor share is Sub-Saharan Africa where nearly 1 in 4 children work (ILO and UNICEF, 2021). Since 2016, global progress in eliminating child labor is at a standstill and the share of children employed in hazardous work even increased (ILO and UNICEF, 2021). Most child labor is concentrated in informal activities in the agricultural sector with an incidence nearly three times higher in rural than in urban areas (ILO and UNICEF, 2021). Only a fraction of working children receives wages and parents are the major employer of children in developing economies (Edmonds and Pavcnik, 2005). It has been noted that focusing on paid child work systematically under-reports the prevalence of child labor, especially that of girls, since unpaid household chores are typically done by girls (Dammert et al., 2018).

In Ethiopia, 44% of the population is below 18 years old and 80% lives in rural areas (CSA et al., 2020). Around 43% of all children are child laborers, with a higher incidence among boys (50%) than among girls (35%) (CSA et al., 2020). Child labor rates in urban areas (15%) are markedly lower than in rural areas (49%) (CSA et al., 2020). Among child laborers, 46% of rural and 47% of urban working children carried out work categorized as hazardous (CSA et al., 2020). Ethiopia's constitutional context prohibits work for children under 14 years of age, which is in line with international standards (CSA et al., 2020). Institutional mechanisms to enforce laws and regulations on child labor have been established by the government but gaps within the authorities of different agencies exist and hinder adequate enforcement (CSA et al., 2020).

This thesis looks at shocks as a potential cause for child labor. The literature divides shocks into two categories, often referred to as covariate and idiosyncratic shocks (e.g. Pradhan and Mukherjee (2018)). However, to avoid any misunderstanding with the econometric use of the terms *covariate* (i.e. independent variable that affects the outcome but is not of direct interest) and *idiosyncratic* (i.e. idiosyncratic error: error that changes over time and across units), I will use the terms community and individual shock. Community shocks refer to shocks that affect many households in the same geographic location. Individual shocks refer to shocks that are specific to one household, with neighboring households not sharing the experience.

Ethiopia is one of the countries most vulnerable to environmental disaster, as it is both highly dependent on sectors like rain-fed agriculture that are sensitive to climatic risk and has a low capacity to adapt to climate change (see e.g. Moges and Bhat (2021) and Conway and Schipper (2011)). The most common natural hazards in Ethiopia are droughts and floods (Cherinet et al., 2022). Since the 1970s, Ethiopia experienced droughts of different intensity at least once every 10 years, while the frequency has increased considerably in the last decades (Cherinet et al., 2022). Over the study period, the drought years of 2006 and 2009 to 2011 stand out as especially dry and as linked to national and supranational famines (see UNCERF (2006), UN News (2009) and OCHA (2011)). Floods also happen relatively regularly in Ethiopia. In the 2000s, flood disasters occurred in five out of ten years, while in the 2010s they occurred in three out of ten years (Cherinet et al., 2022).

In terms of individual shocks, increasing orphan rates are an important concern in Ethiopia. In 2016, 7% of Ethiopian children were orphaned (Ethiopian Central Statistic Agency and ICF, 2016). Several factors could lead to premature adult death. Insufficient nutrition is common, especially in rural areas. In fact, 22% of women and 33% of men aged 15 to 49 are considered thin to the extent of chronic energy deficiency (Ethiopian Central Statistic Agency and ICF, 2016). Moreover, HIV plays a role in premature adult death in Ethiopia, however likely only for the earlier years of the survey period, as Aids-related deaths decreased from 83,000 in 2000 to 15,600 in 2017 (Kibret et al., 2019). Furthermore, the maternal mortality ratio in Ethiopia is high with 401 maternal deaths per 100,000 live births in 2017 (UNICEF, 2019). Note, that these factors also play a role in the prevalence of children with sick parents.

The objective of this thesis is to answer the questions whether children's time use is affected by community and individual shocks, or in other words, if households resort to child labor as a response to shocks. In addition, it aims to identify child and household characteristics that lead to heterogeneous effects. The main results are supplemented by three extensions, namely an analysis of other mitigation channels, an analysis of the longer-term effects of shocks on children's time use and an analysis that differentiates between the various shocks that are grouped together as community and individual shocks in the rest of the paper. These extensions are an attempt to shed more light on the nature of the relationship between shocks and child labor to ultimately be able to draw informed policy conclusions.

The high incidence of child labor in combination with a range of risks faced by households makes Ethiopia a suitable country to study the systematic link between shocks and child labor. To answer the research questions, a panel of 7220 Ethiopian children aged five to fifteen is analysed. The data used stems from four survey rounds between 2006 and 2016. The analysis is made difficult by the fact that both time-invariant and time-varying characteristics, that potentially increase the amount of child labor provided, vary systematically between individuals that experience shocks and those that do not. Data issues pose another source of endogeneity. To address the endogeneity problems, an OLS analysis is complemented by a fixed effects and a difference-in-differences analysis.

This thesis contributes to the existing literature in various respects. Firstly, I consider both time spent on chores as well as time spent on work activities to address that ignoring chores under-reports the time burden on children in general and that of girls in particular (Dammert et al., 2018). Secondly, by analysing which child and household characteristics exacerbate the use of child labor as a response to shocks and by analysing other mitigation channels, I am able to make informed policy recommendations adapted to the situation in Ethiopia. This is important because different economic, legal and environmental contexts may limit the external validity of policy recommendations made for other countries. Third, I distinguish between different shocks and compare their importance, which, to my knowledge, has not been done before in the literature. Lastly, I thoroughly address the issues raised in the literature concerning the difficulty to establish causality when shocks are not random (Bandara et al., 2015).

The remainder of this thesis is structured as follows. Section 2 gives an overview over the literature and derives the hypotheses that will be tested. Section 3 presents the data set and provides summary statistics of the most important variables. Section 4 explains the methodology and the advantages and limitations of the different models. Section 5 presents the results. These include the main results where the overall effect of community and individual shocks are analysed and the analysis of heterogeneous effects. They also include three extensions, namely an analysis of income diversification, access to finance and social networks as possible mitigation channels, an analysis of the effects over time and an analysis of the different shocks that are combined to community and individual shocks. Section 6 discusses the results and relates them to the literature and lastly, section 7 concludes.

2

Theory

2.1 Literature Review

2.1.1 Modelling Framework

The theoretical literature on children's time use is substantial and forms the modelling framework for analysing child labor. Child labor is generally considered within the context of household maximization problems, where the child's and the whole family's welfare, personal characteristics and time and money budgetary constraints determine the child's time allocation to school, leisure and work.

Early work on the topic of household time allocation was conducted by Becker (1965), who provides a model that interprets the household as a single unit of decision making with one shared household utility function. This model is appropriate when it can be assumed that children's bargaining power is limited so that parents decide upon their children's time use (Dehejia and Gatti, 2002). The collective model proposed by Chiappori (1988, 1992) represents an alternative to Becker's unitary model. Here, the household is interpreted as consisting of several individuals with their own utility function searching for a pareto-efficient allocation of time. Specifically, the author models a two stage decision process, in which the non-labor income of the household is first divided between its members according to a predefined rule of sharing which results in individual budget constraints (Chiappori, 1992). Individual consumption and labor supply are then chosen according to these budget constraints. Manser and Brown (1980) present a third class of models, namely bargaining models. The authors look at the household from a game-theory perspective where decisions are not made based on the maximization of utility functions, but based on a bargaining rule agreed upon by the household members that takes into account the individual's utility function[1]. For the two latter models, the relative bargaining strength of the children and factors that influence said strength are of importance.

Models specifically adapted to the analysis of child labor consider various factors underlying child labor, such as poverty, labor and credit market imperfections and household characteristics. The selection of models presented here is not exhaustive, but is rather limited to those that are relevant to this analysis.

[1]It is worth mentioning that Manser and Brown (1980) use their model to analyse marriage decisions. However, they suggest that their work can also build a basis for studying household labor supply.

Seminal work by Basu and Van (1998) assumes a well-functioning labor market in the sense that firms can substitute child labor and adult labor. Their main contribution is the formulation of the luxury axiom, which states that households will only send their children to work if income from alternative sources is not sufficient to meet subsistence levels.

Considering that households can smooth consumption not only by adjusting their labor supply but also by borrowing and saving or through insurance, the importance of credit markets within child labor models becomes apparent. Ranjan (1999) develops a model which shows that child labor in the presence of high returns to education is a consequence of the combination of poverty and credit market imperfections, in particular of the inability of households to take out loans against future earnings. He assumes that households maximize a utility function defined over the current and future consumption. In the current period, the child either attributes to consumption by working or instead accumulates human capital by going to school. Future consumption levels depend on the children's adult wages, where wages of skilled workers who went to school as children are higher than those of unskilled workers. The model yields that all parents, irrespective of their income, send their children to school instead of work if credit markets exist and the return to education is higher than the market rate of interest. In the absence of credit markets, however, only rich parents can send their children to school as poor parents rely on their children for consumption smoothing.

Finally, Bandara et al. (2015) develop a one-period model that takes income shocks into consideration. The model assumes that households derive utility from children's time spent on school as a form of human capital accumulation as well as from consumption. Differently than Ranjan (1999) who assumes two alternative scenarios, one where the child exclusively works and one where the child exclusively goes to school, Bandara et al. (2015) assume that children can combine school and work and that the household's consumption depends on the time share children allocate to work. Additionally, the budget constraint depends on the parent's income, which in turn is affected by random shocks. Consequently, in the absence of insurance, random shocks increase child labor.

2.1.2 Child Labor Literature

The literature on the determinants of child labor is comprehensive and names several factors that influence child labor. Poverty is thereby seen as an underlying condition for the supply of child labor (see e.g. Posso (2020), Edmonds and Pavcnik (2005) and Edmonds (2007)). As mentioned above, the luxury axiom names poverty as the reason of child labor (Basu and Van, 1998). It states that child labor is employed to ensure a minimum level of family consumption in the case that parents' income is insufficient to do so. The diminishing marginal utility of children's income contribution, meaning that the contribution of the child's additional income to the overall household wellbeing is higher the lower the family's income, reinforces the systematic link between poverty and child labor as the utility of children's additional income and consequently the incentive to use child labor decreases when the household income increases (Edmonds and Pavcnik, 2005). The wealth paradox described by Bhalotra and Heady (2003) directly challenges the luxury axiom and the idea that poverty causes child labor. It is rooted in the empirical observation that children of land-rich households are more likely to work than children of land-poor households in some developing countries. Empirical evidence for this second line of reasoning which argues that access to productive assets, which are not available to the poorest households, provide employment opportunities and encourage the employment of children among poor households is for example provided by Cockburn and Dostie (2007) and Frempong (2020) for Ethiopia and Malawi respectively. Basu et al. (2010) offer a model that can reconcile the two opposing arguments. They argue that the relationship between poverty and child labor can be described by an 'inverted U'-shape, where child labor increases with household land holdings or family businesses, i.e. employment opportunities for children, and declines as soon as the income effect dominates.

Within a context of poverty, negative income shocks caused by individual or community shocks increase the incidence of child labor (see for example Duryea et al. (2007), Beegle et al. (2006), Bandara et al. (2015) and Dehejia and Gatti (2002)). Especially given that many developing countries lack social protection and in the context of credit and insurance market imperfection, poor households are both more vulnerable towards risk and less equipped to deal with risk (Banerjee and Duflo, 2007). As poor families may lack other instruments to deal with income shocks, they might turn to child labor to provide some additional income after a negative income shock. The increase of child labor as a response to negative shocks was empirically confirmed. An early paper by Jacoby and Skoufias (1997) finds that farm households in India adapt their children's school attendance to react to anticipated and non-anticipated income shocks, indicating that child labor plays a role in reacting to shocks. Duryea et al. (2007) find that income shocks in the form of unemployment of the household head significantly increase the probability of children to enter the labor market in urban Brazil and Beegle et al. (2006) find that crop shocks significantly increase child labor in Tanzania. Focusing on Tanzania as well, Bandara et al. (2015) differentiate between experiencing a household death or a crop shock as well as between time spent on work and on household chores. They find that boys only significantly increase their time spent on chores when the household is hit by a crop shock but not when experiencing a household death. Girls on the other hand show no significant changes in the case of a crop shock, but significantly decrease their time spent on chores in case of a household death. In terms of work, the authors find that experiencing either of the two shocks only significantly increases the work time by boys, not by girls. Note that the authors emphasize that results regarding experiencing a death in the household are unlikely causal. Finally, studying child labor in a cross-country framework, Dehejia and Gatti (2002) specify that households only use child labor as a coping mechanism against income variability[2] in countries where financial markets are not developed.

The literature identifies other factors that can increase child labor. Given the limited extent of this paper, I will only mention them briefly. For one, the quality of available schooling matters. If the returns to schooling are perceived to be small compared to the returns to work, child labor supply might increase (Dammert et al., 2018). Decisions regarding children's schooling can hereby be thought of as a trade off between immediate income benefits and future benefits of educational investment (Edmonds, 2007). For another, a specific demand for child labor might

[2]Income variability is here proxied by the standard deviation of annual GDP growth in the previous 5 years, thus only being partly comparable with a household income shock.

exist. Seasonally varying labor demand of family farms could make it easier and less costly to employ children than to engage in employing and laying off adult labor according to the labor demand fluctuations (Bhalotra and Heady, 2003). Moreover, poorly developed wage labor markets might prevent households with family farms or businesses from hiring adult workers and lead them to employ their children instead (Bhalotra and Heady, 2003).

The literature on the consequences of child labor focuses mostly on health and education outcomes. While substantial evidence for an association between child labor and detrimental health outcomes, such as higher prevalence of injuries, diseases due to harmful exposure and worse nutritional and mental health status exists, causal relations are less established (Ibrahim et al., 2018). Nevertheless, Edmonds (2007) points out that, especially considering that working children tend to live in households with lower income and household consumption, additional income and resources due to child labor might improve health and nutrition so that the returns of child labor to health could be overall positive.

Child labor can negatively affect the individual's education. Beegle et al. (2009) for example find both a reduced probability of being enrolled in school as well as a reduction in educational attainment in terms of highest completed grade for child workers in Vietnam. Further, an analysis of nine Latin American countries finds that children that often combine work and school score significantly lower on language and math tests. This could be due to missing classes but possibly also due to exhaustion or not being able to spend as much time on homework (Gunnarsson et al., 2006). Lee et al. (2021) confirm this finding for ten francophone Western and Central African countries.

However, child labor does not strictly reduce the child's future human capital and earnings ability. If child labor provides vocational training or general workplace experience, child work might also increase the individual's human capital (Emerson and Souza, 2011). Furthermore, working might be necessary to finance the child's education and combining school and work might thus be a beneficial decision. Emerson and Souza (2011) refute this hypothesis for young children but not for older children, as they establish that the effect of child labor on the future earnings ability of children in Brazil is negative, especially for boys, but that the effect becomes positive around the age of 14. Opposing this, Posso (2017) finds that child workers, including those that start working after age 13, have worse earning outcomes as adults.

Another issue worth mentioning is the inter-generational persistence of child labor. Emerson and Souza (2003) construct an overlapping generations model to explore child labor traps as the reason for inter-generational persistence of child labor. They assume the child's education to be a function of the parent's human capital. If the adult's human capital is below a certain level, the child will work and accumulate less human capital than the parent and the household will eventually reach a steady state where the child always works and never goes to school. The authors find empirical evidence for this, but suggest that factors beyond education connecting parents' and children's child labor experience exist. Thus, by driving child labor in the next generation, child labor can not only be interpreted as a consequence but also as a cause for poverty.

2.1.3 Shock Literature

Households in developing countries are especially vulnerable to risk. This is because average incomes are low as well as more volatile, especially in rural areas, which makes households more prone to shocks and less equipped to deal with them (Banerjee and Duflo, 2007). Among others, households could be hit by environmental shocks, such as drought, flood and erosion, by individual damages like unemployment, theft, robbery and destruction of crops, or by shocks related to sudden changes in the household situation, for example related to illness and death (Pradhan and Mukherjee, 2018). It is worth mentioning that shocks might not only impact children's time use through their effect on the household's income. Instead, shocks could affect children by decreasing the amount of the arising work and chores that can be provided by the adults in the household. Especially in the case of death or illness of a parent, children's time allocation might be affected by a substitution effect rather than an income effect. Literature on the effect of parental death on schooling confirms that children take over tasks previously provided by the ill or deceased parent (Yamano and Jayne, 2005).

Households, especially those that are affected by credit and insurance market imperfections, use different strategies to deal with risk, which can be divided into ex-ante strategies, i.e. income smoothing strategies, to reduce the risk of being hit by shocks and ex-post strategies, i.e. consumption smoothing strategies, to deal with the consequences of shocks (see for example Morduch (1995) and Dercon (2002)). Ex-ante strategies include the diversification of income activities and assets, migration and a pivoting towards low-risk activities (Morduch, 1995). Ex-post strategies include borrowing and saving, the sale of assets, the adjustment of labor supply and (informal) insurance arrangements (Morduch, 1995). Overall, the literature suggests that these strategies only work to a certain extent (Dercon, 2005). Dercon (2002) emphasizes that especially informal strategies that rely on local risk sharing networks can not insure against community shocks nor alleviate its consequences as everyone is affected.

Child labor is part of the ex-post strategies since it constitutes an adjustment of the household labor supply. The literature on the relation between household labor supply and income shocks is rather limited. Kochar (1999) and Cameron and Worswick (2003) provide evidence that households in developing countries use the labor market to smooth consumption when faced with crop shocks. Specifically, they show that households in India and Indonesia respectively reallocate labor from their own farm to the market, which reflects a shift to a more productive use of time. Both use inter-temporal consumption models in which consumption and labor supply decisions are made by the household as a single decision-making unit and where the income shock enters the model in the form of reduced farm profit. Kochar (1999) uses a two-period model, while Cameron and Worswick (2003) applies a life time model. Neither of the studies specifically addresses the use of child labor for consumption smoothing.

The research on other mitigation channels is more comprehensive. Since I will focus on income diversification, access to finance, and social networks as possible measures to mitigate the effects of shocks on children's time use, the literature review below will be focused to these coping strategies.

Financial access, and most importantly access to credit, can be seen as a substitute for insurance (Dercon, 2002). It allows households to smooth away any impacts of shocks by borrowing and saving so that changes in their income should not affect their consumption (Morduch, 1995). It is worth noting that certain individuals might be excluded from accessing credit or other market-provided financial instruments (Pradhan and Mukherjee, 2018). Empirical evidence confirms that families that have access to credit or other financial instruments do not resort to or increase child labor when faced by income variability (Dehejia and Gatti, 2002).

Where formal credit does not exist, households might turn to other strategies to spread risk. Diversification of income sources is one such way of income smoothing (Morduch, 1995). As long as the different income sources are not perfectly correlated, the risk of an income shock is reduced (Dercon, 2002). Households might for example take on part-time jobs outside of agriculture to avoid being exposed to farming or environmental risks, while they stay in farming to be less dependent on their other jobs (Banerjee and Duflo, 2007). Three caveats that could lower the functioning of this mitigation strategy are worth mentioning. Firstly, diversifying income sources might signify allocating time to low-risk but simultaneously low-return activities, so that lowering risk might go hand in hand with lowering income (Dercon, 2002). Secondly, while farm and off-farm activities are often uncorrelated in normal times, they might be correlated when shocks occur, for example when agricultural input factors lower production capacities in the industry, or when the demand for off-farm products is reduced during times of shock (Dercon, 2002). This would lower the effectiveness of income diversification as a mitigation strategy. Thirdly, entry constraints to the labor market, such as capital or skills could make income diversification complicated (Dercon, 2002).

Lastly, social networks could mitigate the effect of shocks on the household. Informal arrangements are observed within extended families, ethnic groups, neighborhoods and professional networks (Dercon, 2002). Evidence exist for support in terms of financial and non-financial resources. For instance, Dercon et al. (2006) describe indigenous funeral groups in rural Tanzania and Ethiopia that provide financial support in times of household death based on the affiliation to women's neighborhood or religion based groups. The importance of non-financial kinship support in Sub-Saharan Africa is often emphasized in the context of taking care of children with deceased parents (see Case et al. (2004) for a literature review).

2.2 Hypotheses

Building on insights from the literature review, the following hypotheses can be derived.

1. Children increase both their time spent on chores and work when they are hit by either a community or individual shock.

The hypothesis is not new when relating shocks to work hours and is for example confirmed for Brazil and Tanzania by Duryea et al. (2007), Beegle et al. (2006) and Bandara et al. (2015). However, only Bandara et al. (2015) specifically mention the time burden of chores. Moreover, results may vary based on the different environmental, constitutional and economic context in Ethiopia.

2. The amount and significance of the increase varies across children and household characteristics.

Heterogeneous effects can be expected for a number of observable characteristics. Firstly, the fact that traditional gender roles often prevail leads to the expectation that girls tend to increase their time spent on chores while boys tend to increase their time spent on work when hit by a shock (Dammert et al., 2018). Secondly, I expect older children to increase their time spent on work and chores more than younger children. This is motivated by the idea that older children are more capable of taking on extra work or chore burdens. Global child labor estimates confirm a higher prevalence for child employment for older children (ILO, 2016). Thirdly, I expect that poor children have to adapt their time use more than richer children when hit by a shock. The comprehensive research on the connection between risk and poverty concludes that poor households are constrained in their strategies to cope with shocks ex-post and ex-ante (see for example Banerjee and Duflo (2007) and Dercon (2005)). In addition to the different coping strategies available to households, the relative impact of shocks also varies by poverty level. Shocks might only reduce the consumption of poor households to subsistence levels, not that of rich households. Models which assume that households only use child labor to ensure subsistence levels (e.g. Basu and Van (1998)) would subsequently not expect children from rich households to increase their work time. Lastly, I expect children from rural areas to be more affected by shocks than children from urban areas. This might specifically apply to community shocks, as environmental shocks likely have a bigger impact on households that engage in farming. Specifically, as Ethiopia engages predominantly in rain-fed agriculture, changes in the average amount and timing of rainfall has important impacts on rural areas (Conway and Schipper, 2011). Beyond this, rural areas are more deprived of credit markets that could alleviate the effect of shocks (Demirgüç-Kunt et al., 2022)[3].

3. Children from households that have good social networks and financial access and diversify their income are less affected than other children when hit by a shock.

Social networks, financial access and income diversification are named in the literature as factors that potentially alleviate the effect of shocks on households (see e.g. Morduch (1995), Dercon (2002) and Dercon (2005)). Therefore, it can be assumed that all three channels significantly reduce the increase in child work that occurs after a shock. One further distinction can be made. I expect the mitigation channel of social networks to be less pronounced for the effect on time spent on work than on chores. The opposite is expected for the mitigation channels of financial access and income diversification. To illustrate the reasoning of this, consider that the two latter channels primarily tackle the economic consequences of a shock. As the child's income is a deciding factor why parents would send their children to work, any mitigation channel that directly lowers the need for the child to provide an income most probably also lowers the child's increase of time spent on work. The channel of social networks on the other hand is not only related to monetary support but also to other types of help a household could receive after a shock. In particular, social

[3]In all of the 23 countries for which data was available in 2021, account ownership shares were lower for individuals living in rural areas than for individuals from urban areas. The same is true for the share of people that borrowed any money from a formal financial institution or using a mobile money account with the exception of The Republic of Congo, Guinea, Liberia, Malawi and Sierra Leone (Demirgüç-Kunt et al., 2022).

networks might support a household by providing time instead of money. Chores, for example, such that were previously provided by a sick or deceased parent or by a parent who had to reallocate time from unpaid to paid work, might hereby be more willingly taken on by adults outside of the household than work.

4. Shocks have persistent effects on children's time use so that their working and chore hours are elevated even when the shock happened in an earlier survey round.

This hypothesis is motivated by the finding that child labor reduces the adult earning capacity under certain conditions (see e.g. Emerson and Souza (2011) and Posso (2017)).

5. The different types of shocks, which are grouped together into individual and community shocks, vary in their impact on children's time spent on work or chores. Moreover, some types of shocks might be more relevant for the overall effect of community and individual shocks than other shocks.

The literature does not allow for differentiated hypotheses concerning the various community shocks. However, a few conjectures can be made about individual shocks. For one, if the assumption of traditional gender roles holds, it is likely that the illness and death of a father has a bigger effect on children's work time, as the household lost the main income provider, whereas the illness and death of a mother has a bigger effect on children's chore time, as the household lost their main childcare provider. For another, a new birth can be expected to predominantly increases the time spent on chores, since children might not only have to take over tasks that were previously performed by the baby's caregiver, but the overall amount of chores might increase as well.

3

Data

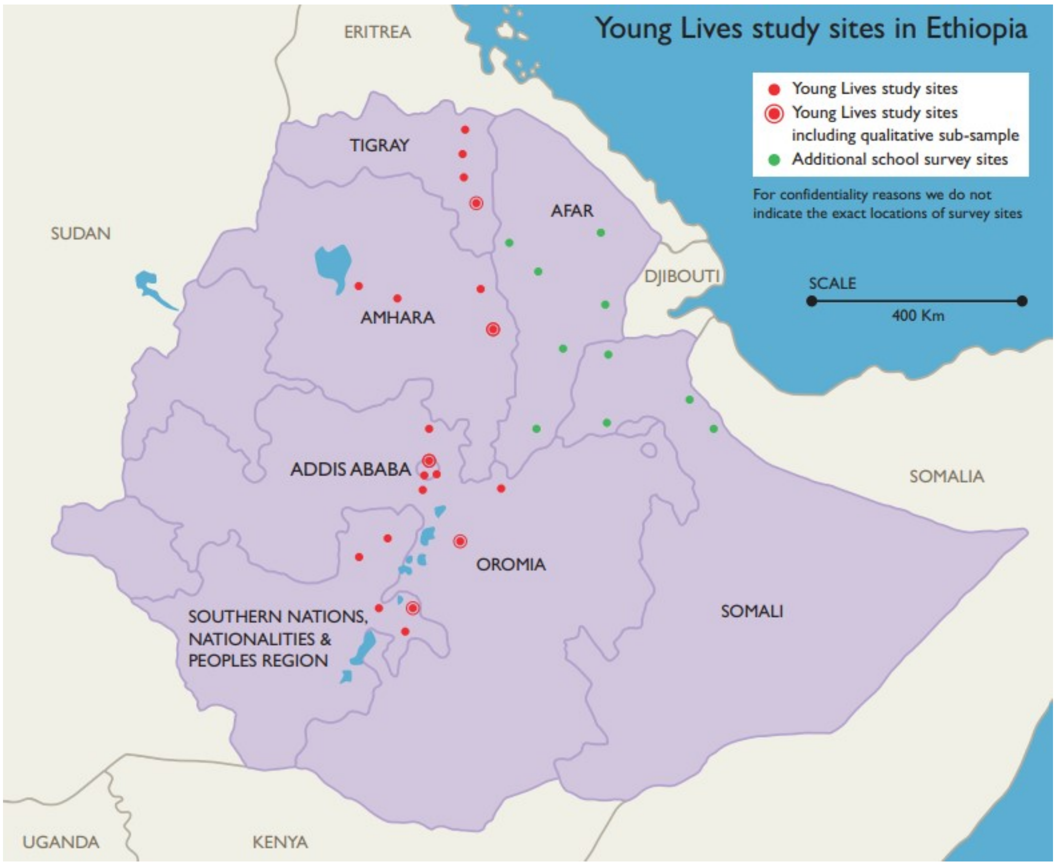
3.1 Data Sources

The data used in this analysis comes from the Young Lives (YL) study, a longitudinal cohort study core-funded by UK aid from the Department for International Development (DFID) and co-funded from 2010 to 2014 by The Netherlands Ministry of Foreign Affairs. The goal of the study is to investigate the changing nature of childhood poverty in four low- and middle-income countries, namely Ethiopia, India, Peru and Vietnam. The project contains both household and child-level data for 12,000 children, collected in five rounds over the course of 15 years (2002, 2006, 2009, 2013, 2016). Children from a younger cohort were one year of age when their caretakers were interviewed for the first time, whereas children from an older cohort were first interviewed at age eight (Briones, 2018). Information was not collected for all children in the household but specifically for those that were one or eight years old in 2002 and qualified as the "Young Lives child".

This analysis focuses on Ethiopia. 20 sentinel sites were selected based on three criteria, namely national coverage, a balanced representation of rural and urban districts and the possibility of finding at least 100 households with a child aged one and 50 households with a child aged eight in that area (Outes-Leon and Sanchez, 2008). The five regions (Amhara, Oromia, Southern Nations, Nationalities and Peoples (SNNP), Tigray and Abbis Ababa) in which the study was conducted account for 96% of the national population, thus fulfilling the first criterion (Young Lives, 2018). Given the aim of the study, the sampling of the sentinel sites purposely produced an oversampling of food-deficient districts as well as a pro-poor selection bias. Within the sentinel sites, households containing children in the right age groups were randomly selected. Thus, the study is not nationally representative (Young Lives, 2018).

The dataset is restricted in the following ways. Firstly, as the children of the older cohort are older than 18 years during the 4th and 5th interview rounds, only the younger cohorts in these rounds are considered for the analysis. Secondly, questions asked during interviews varied for the different rounds. Unfortunately, no information on shocks nor on time use is available for round 1 of the study, so the dataset is restricted to rounds 2 to 5. Thirdly, the dataset is restricted to only those children that have no missing information on shocks and on time spent on work and chores. The remaining dataset contains 8835 observations, of which 2310 come from round 2 (Boyden, J., 2022a), 2856 from round 3 (Boyden, J., 2022b), 1867 from

Figure 3.1: Young Lives study sites in Ethiopia



Source: Young Lives (2018)

round 4 (Duc et al., 2022a) and 1802 from round 5 (Duc et al., 2022b).

3.2 Variable Description

The main variables of interest are two shock variables and two time-use variables. Information on shocks was acquired by asking households which shocks among a predefined list of 27 separate events negatively affected the welfare of the household (Briones, 2018). From this, I construct the variables of interest in the following way: The dummy variable *Community Shock* takes on the value 1 if a child's household experienced any environmental shock (drought, flooding, erosion, frost) or any shock related to pests (on crops (including crop failure), livestock or storage), and 0 otherwise. The variable *Individual Shock* takes on the value 1 if a child's household experienced any crime (theft or destruction of cash, crops, livestock or housing), any shock to their house (fire or collapse), or family shock (death of the father or mother, illness of the father or mother, divorce or separation), and 0 otherwise. Two drawbacks to the variables are worth mentioning. Firstly, the data on shocks does not directly indicate if a shock occurred or not. Rather, it reflects whether the household perceived an event to be negative for its well-being. Secondly, households are asked to list any shocks that occurred since the last interview round. As interview rounds lay between 3 and 4 years apart, recalling errors could pose a substantial problem. In particular, shocks that occurred shortly after the previous survey round might be understated[1]

Information on children's time allocation is collected by asking the amount of time a child spends on eight different activities (sleep, school, studying, play, work, chores, care and tasks) on a typical weekday (Briones, 2018). I construct the variable *Time worked* as the amount of hours a child spends on tasks or remunerated work. Tasks are defined as work inside the household which generates income, including farming, cattle herding, shepherding and participating in other family businesses. Work is defined as paid activities outside of the household including travel time to and from work. The variable *Time chores* is constructed as the amount of time spent on helping at home (fetching water or firewood, cleaning, cooking, washing, shopping) and on taking care of other household members. The literature on time use research notes that the use of stylised survey questions provides less accurate data than time diary studies, where respondents are asked to report exactly what they did each hour during a representative day (Marini and Shelton, 1993). Following Stinson (1999), who states that estimates based on stylised survey questions are likely distorted due to respondents providing socially desirable answers, I would expect hours spent on work to be understated for younger children. The direction of any mismeasurements, however, cannot be known with certainty.

For the analysis of mitigation strategies, three variables are of interest, namely *Social Networks, Financial Access* and *Income Diversification.* The first variable is a categorical variable taking on the values 1 to 7 depending on the number of people the household can rely on in time of need for material or financial support (1=1-2 people; 2= 3-5 people, 3=6-10 people, 4=11-15 people, 5=16-20 people, 6=21-30 people, 7=over 30 people) (Young Lives, 2014). The second variable is a dummy taking on the value of 1 if the household is situated in a community that has access to credit or finance through public banks, private banks, local government credit, agricultural cooperative societies or microfinance institutions, and 0 otherwise. Information on access to services was not acquired by interviewing households but rather by interviewing three community informants, for example elected people representatives, health workers, teachers, religious leaders, community leaders or community elders (Young Lives, 2014). The last variable is constructed by counting from how many different sources the household draws its income. Forms of income include the sale of livestock or livestock products, work for wages (agricultural, salaried, casual or food-for-cash work), business income such as profits from commodities, processed food, handicrafts, carpentry and services, income from land used/not used for crops, income from foresting and income from fishery (Young Lives, 2014). If any household member had earned any income from one of these activities in the last 12 months, 1 is added to *Income Diversification.* One disadvantage of this measure is that is does not allow to draw conclusions about the labor allocation between these activities, meaning that a household may well have access to many income sources but continue to draw the bulk of its income from one source and therefore remain heavily dependent on that source. Additionally, data

[1] This is mainly problematic if the effect of shocks on children are not temporary but persistent. Any increase of children's time use after a shock that is not reported would increase the average working hours in the group of children that is considered not to have experienced a shock. Consequently, the estimated difference between the treated and non-treated group will be smaller than in reality, making the reported results conservative estimates. In section 5.3.2 I show that there is no evidence for shocks having persistent effects on children's time use, so that this issue can be assumed to be negligible.

on income diversification was not recorded for the 5th survey round.

The last variable of interest that requires some explanations is the wealth index, which is used to control for the socio-economic status of households. I use the already constructed data from the rounds 1-5 Constructed Data Files (Boyden, J., 2022c) that is based on three indices, namely housing quality, access to services and ownership of consumer durables (Briones, 2017). The index takes on a value between 0 and 1, with 1 indicating the highest socio-economic status. The Young Lives technical reports propose the categorization of Ethiopian households into three groups, where households are considered "very poor" if the wealth index is smaller than 0.2, "poor" with a wealth index between 0.2 and 0.4 and "less poor" when their wealth index is bigger than 0.4 (Briones, 2017). Note that the wealth index is only a simple average of the three indices and assumes that they are equally important (Briones, 2017).

3.3 Summary Statistics and Correlations

Table 3.1 provides summary statistics. As can be seen, the sample contains slightly more boys than girls. The average age in rounds 4 and 5 is 12 and 15, which is related to the fact that only children from the young cohort are considered in these rounds. In rounds 2 and 3 the average age is 8 and 10 years respectively. About 64% of the sample lives in rural households. The average household has a wealth index of 0.36 which is considered poor in Ethiopia. In particular, the distribution of households is roughly equal across the categories "poorest", "poor" and "less poor" in the second round, but splits up over time. While the share of poor households increases slightly, the share of less poor households increases substantially and the share of poorest households decreases. The hours spent on work increase over time on average. Activities in self-employment make up the biggest part of the work provided. This is not surprising considering that the average age increases with each round. The average time spent on chores increases from round 2 to round 3, decreases afterwards and increases again slightly in round 5. All in all, doing chores is more common than working, with 81% of the sample reporting spending some time on chores while only 42% reported spending some time working. Note, that the high share of children that do not work at all explains the low average amount of children's working hours in the sample. 43% of the total sample experienced a community shock. For those experiencing community shocks, it was generally more common to experience an environmental shock than a shock related to pests, with households being specifically affected by environmental shocks in rounds 2 and 3. Roughly the same share of children suffered from individual shocks, of which most were affected by a family shock. As for the mitigation variables, the average household had about 3 to 5 people to rely on in times of financial difficulty. 90% of households reported to have access to finance and the average household drew income from three different activities.

Table 3.1: Summary Statistics

	Ethiopia				
	Round 2	Round 3	Round 4	Round 5	Total
Male (%)	53	52	53	53	53
Age (years)	7.96	10.39	12.00	15.00	11.03
Rural (%)	65	64	63	63	64
Wealth Index[a]	0.31	0.36	0.39	0.42	0.36
- Poorest (%)	36	24	17	10	23
- Poor (%)	31	36	37	39	36
- Less Poor (%)	34	40	46	51	42
Providing any work (%)	30	43	48	49	42
Hours work (per day)	1.02	1.60	1.63	1.84	1.50
- Employed (h per day)	0.07	0.15	0.07	0.27	0.14
- Self-employed[b] (h per day)	0.95	1.45	1.56	1.57	1.37
Doing any chores (%)	60	87	87	91	81
Hours chores (per day)	1.86	2.76	2.46	2.72	2.45
- Caring for HH members (h per day)	0.54	0.78	0.64	0.52	0.64
- Household chores (h per day)	1.31	1.98	1.82	2.20	1.82
Community Shock[c] (%)	47	52	30	34	43
- Environmental Shock (%)	40	42	22	26	34
- Pest Shock (%)	26	35	26	26	27
Individual Shock[d] (%)	51	55	37	24	44
- Criminal Shock (%)	12	10	9	3	9
- House Shock (%)	3	2	1	1	1
- Family Shock (%)	45	50	31	22	39
Social Networks[e]	1.90	2.29	1.99	2.25	2.12
Financial Access (%)	90	84	93	100	90
Income Diversification[f]	2.62	2.59	4.71	/	3.16
N	2310	2856	1867	1802	8835

Note: For variable descriptions see section 3.2.
[a] Cutoff points: < 0.2 very poor, $0.2 - 0.4$ poor, > 0.4 less poor; [b] i.e. farming or family business; [c] Environmental Shock: drought, flooding, erosion, frost; Pest Shock: pests on crops (including crop failure), livestock or storage; [d] Criminal Shock: theft or destruction of cash, crops, livestock or housing; House Shock: fire or collapse of the house; Family Shock: death of the father, mother or other household member, illness of the father, mother or other household member, or divorce or separation; [e] Number of people household can rely on in times of financial need (1=1-2 people; 2= 3-5 people, 3=6-10 people, 4=11-15 people, 5=16-20 people, 6=21-30 people, 7=over 30 people); [f] Number of different activities any household member earned money from during the last 12 months.
Source: Own calculations based on Young Lives rounds 2-5 and Rounds 1-5 Constructed Files.

4

Methods

4.1 Baseline Model

To analyse the effect[1] of shocks on children's time allocation, the following OLS model is applied:

$$Y_{it} = \beta_0 + \beta_1 Shock_{it} + \beta_2 Age_{it} + \beta_3 Male_{it} + \beta_4 WealthIndex_{it} + \beta_5 Rural_{it} + Controls_{it} + u_{it} \tag{4.1}$$

Y_{it} denotes the outcome, that is hours spent on work or hours spent on chores. The variable *Shock* either refers to community or individual shocks, following the categorizations presented in section 3.2. Consequently, β_1 is the coefficient of interest. The controls for age, gender, wealth and rural location can be seen as standard controls. *Age* is hereby a vector of dummies for the ages 8, 12 and 15, with age 5 as the excluded baseline category. For an explanation of the variable *Wealth Index*, see section 3.2. *Male* and *Rural* are dummies taking on the value 1 if children are male and live in a rural area respectively, and 0 otherwise.

Other controls include dummies for survey rounds 2 to 4, with round 5 as the excluded baseline category. The variation in the round dummies is due in part to the age of the child and in part to the specific year of the survey rounds. Although the age dummies already control for any variation due to age, the round controls are added to further control for any variation stemming from the different survey years.

Literature on the determinants of children's time allocation motivate the choice of personal and household controls. Personal controls include a dummy for being the oldest child in the household and the child's relation to the household head. The first control is motivated by the assumption that older siblings start working or providing chores before their younger siblings, regardless of the age. Hence, younger siblings are assumed to start working later in life than older siblings. Cockburn and Dostie (2007) provide empirical evidence that the sibling composition matters for the time allocation to work by Ethiopian children. The latter control is linked to the argument made by biologist W.D. Hamilton who hypothesized that altruistic behavior between individuals is an increasing function of the degree of genetic relatedness between the individuals (Hamilton, 1964). In a household decision framework this could mean

[1] In the following, I will use the word *effect* to refer to parameter estimates. This does not necessarily imply a causal relationship. To provide clarity, I will refer to the parameter estimates of models that are considered causal as *causal effects*.

that household heads are likely favoring their own children over children that are more distantly related. In addition, controls for the child's religion and ethnicity are included. These control for any cultural differences that result in differing views for example regarding the role of girls in the household or the importance placed on activities outside of work and chores such as schooling (see for example Edmonds and Pavcnik (2005)'s literature review and Mitra (2020) for a qualitative study).

Household controls include the region to control for any differences in the labor market and policy differences, that might affect decisions for children to work, to go to school, or to spend their time otherwise. Following the discussion between Basu and Van (1998) and Bhalotra and Heady (2003) mentioned above, the amount of land owned by the household is controlled for. Another agrarian asset linked to employment opportunities for children in this context is livestock (Basu et al., 2010). A dummy indicating the ownership of any livestock is thus included in the controls. Edmonds and Pavcnik (2005) and Dammert et al. (2018) emphasize the importance of the availability of schools for the time allocation decision between school and work or chores, so a dummy for school availability is also included as a household control. Further, the importance of parental human capital in child labor decisions is mentioned by Emerson and Souza (2003) which motivates controlling for the education of the caregiver. Lastly, the gender of the caregiver as well as the household size are controlled for. This is motivated by the literature on children's resource shares within the family, and the role played by family (gender) structures in this context (see e.g. Duflo (2003) and Buvinic and Gupta (1997)). It is important to note that the control for the gender of the caregiver is not included in the analysis of individual shocks. This is because family shocks include the death or illness of the father or mother respectively, so that controlling for the gender of the caregiver might take up much of the effect of the gendered shock.

Standard errors are clustered at the individual level for the analysis of individual shocks and at the community level for the analysis of community shocks. Using clustered standard errors relaxes the assumption of independent residuals and allows standard errors to be correlated within clusters (Moulton, 1986). More precisely, the estimators for the variance of the estimated coefficient is usually biased downward when residuals are correlated within clusters, an issue that is fixed by using cluster-robust standard errors (Cameron and Miller, 2015). This is crucial in order to get accurate statistical inference, as resulting standard errors and p-values would otherwise be too small. Concerning the level of clustering, Cameron and Miller (2015) suggest to choose the most aggregate level feasible. Generally, it should be clustered at the level where residuals are correlated at, which in this case would be the level of treatment assignment, that is the community level for community shocks and the child level for individual shocks[2]. To check whether clustering makes a difference in the interpretation of the results and is not just a theoretical issue, I compare the results of the baseline model when using clustered and heteroskedasticity robust standard errors[3]. The results can be found in table A.3. While the estimated coefficients are not affected by the use of clustered or non-clustered standard errors, their significance is. In line with econometric theory, the clustered standard errors are

[2]A more aggregate level of clustering in the case of individual shocks would be the household level. However, note that only one child was interviewed per household so that the household corresponds to the child level.

[3]Keep in mind that clustered standard errors are simultaneously robust to heteroskedasticity.

bigger than the robust standard errors, which leads to coefficients being significant at higher significance levels. For example, in the analysis of children's time spent on chores, the estimated coefficient of the community shock is significant at the 1% level when robust standard errors are used but only at the 10% level when clustered standard errors are used. Furthermore, the effect of individual shocks on children's time spent working is significant at the 1% level when robust standard errors are used but otherwise only at the 5% level. Thus, clustered standard errors are used in the following.

Below, OLS results are presented in three specifications, where the first is an empty model that only controls for the rounds, the second specification adds personal controls and the third specification includes round, personal and household controls. As not all observations have data for the full set of controls, the sample is reduced to 7220 observations in the third specification. To ensure that the differences between specifications are due to the addition of more controls and not driven by the non-randomness of missing data, I run the empty model on both the original sample and a sample containing only the 7220 observations with information on all control variables. Tables A.1 and A.2 show the results. As the estimated effect of the community shock differs significantly when running the empty model on the original and restricted sample, I will run all further regressions on the restricted sample.

It is not possible to establish causality with the OLS regressions as both time-invariant and time-varying unobserved heterogeneity[4] could bias the regression results. Examples for time-invariant factors that could cause endogeneity issues in the analysis of shocks and children's time use include genetic conditions and deep-rooted, time-invariant behavior and norms that simultaneously influence receiving a shock (for example illness or death within the household) and the ability, need or willingness to spend time on work or chores. Bias due to time-varying factors arises if the explanatory shock variable is correlated with the idiosyncratic error. One example of such a source of endogeneity is the omittance of the parental health status in the analysis of individual shocks. Having a sick parent could determine the time spent on work or chores while it is also correlated with receiving an individual shock, as parental death might be preceded by an illness. In this example, children would increase their working hours even before the parental death to compensate for their sick parent. The difference between the working hours provided before the shock and after the shock is thus reduced compared to a situation where parental health status is controlled for. The resulting bias would hence be negative meaning that the results from a model that does not control for time-varying confounders are conservative estimates. In contrast to individual shocks, it can be argued that community shocks are exogenous, as they are random events. However, the way the data was obtained, that is by asking for respondents' individual assessment of whether or not they had been affected by a shock instead of determining if a community shock occurred or not, gives way to endogeneity problems. Bias would occur when the probability of reporting being hit by a community shock increases with certain unobserved characteristics.

Given these endogeneity problems, the results of the baseline model are merely intended to show basic associations. To alleviate potential bias, two other models are applied, namely a fixed effects model and a matched difference-in-difference model.

[4]Unobserved heterogeneity describes the existence of unobserved differences between individuals that are associated the the observed variable of interest.

The strengths and weaknesses of these models are explained hereafter.

4.2 Fixed Effects Analysis

Using a simple OLS model might be insufficient, as unobserved heterogeneity can cause endogeneity problems and consequently biased results. Take a model, where the composite error η_{it} is made up by the time-invariant part a_i and the idiosyncratic error u_{it} that varies over time and across individuals:

$$Y_{it} = \beta_1 x_{it} + \underbrace{a_i + u_{it}}_{\eta_{it}} \tag{4.2}$$

If the endogeneity problem arises from the time-invariant part of the composite error only, that is if $Cov(a_i, x_i) \neq 0$ but $Cov(u_{it}, x_{it}) = 0$, fixed effects (FE) estimation produces consistent estimates of causal effects because any time-invariant unobserved heterogeneity is removed by applying a within transformation (Wooldridge, 2012). More specifically, for each individual i the average over time is subtracted from equation 4.2.

$$Y_{it} - \bar{Y}_i = \beta_1(x_{it} - \bar{x}_i) + (u_{it} - \bar{u}_i) \tag{4.3}$$

where $\bar{Y}_i = T^{-1} \sum_{t=1}^{T} y_{it}$ and so on (Wooldridge, 2012). Note that any time-invariant factors are removed from the model as a_i is equal to $\bar{a}_i$. The within estimator $\tilde{\beta}_1$ is obtained by running OLS on equation 4.3 and implicitly controls for any factors that are constant over time. Note that this also includes not only unobserved but also observed time-invariant factors such as the child's gender.

Before using the FE model, I assess whether it should be preferred over a Random Effects (RE) model. RE models assume that the time-invariant and unobserved effect a_i is uncorrelated with each explanatory variable (Wooldridge, 2012). To confirm that this is not the case, I run a Hausman Test, where the null hypothesis states that the unique errors are not correlated with the regressors. The test results are shown in Figures A.1 and A.2. The null hypothesis can be rejected and it can be assumed that FE estimators are consistent and should be preferred over RE estimators.

The model chosen for the FE analysis takes on the following form:

$$Y_{it} = \beta_0 + \beta_1 Shock_{it} + \beta_2 Age_{it} + \beta_3 WealthIndex_{it} + \beta_4 Rural_{it} + Controls_{it} + a_i + u_{it} \tag{4.4}$$

where a_i is the time-invariant error term and u_{it} the idiosyncratic error term. The same controls as in the baseline model are used (see section 4.1). It should be noted that the controls for the child's gender, ethnicity and religion are eliminated, as they are time-invariant. Note also, that to avoid perfect multicollinearity between the round and age dummies, only the dummy for one round can be included in the FE model.

As in the OLS specification, standard errors are clustered at the child level for the analysis of individual shocks and at the community level[5] for the analysis of

[5]Note that the panels are not nested within community clusters in the FE specification, meaning that at least one individual appears in more than one community. That could easily be the case if individuals move to different communities. The option -xtreg, nonest- allows the calculation of clustered variance post FE, even if the panels are not nested, and is applied in the FE specifications that analyse the effect of community shocks.

community shocks. Even though fixed effects eliminate within-cluster correlation of residuals at the level of the fixed effects (Cameron and Miller, 2015), Abadie et al. (2017) show that clustering might matter. They conclude that beyond clustering in sampling or assignment, of which the latter is the case here as receiving the shock is potentially determined by characteristics that vary over clusters, heterogeneity in the treatment effects is required for clustering to be necessary. As will be shown in section 5.2, the treatment effects are heterogeneous, as the variability of direction and magnitude of the effect of shocks is non random and can be explained for example by age and gender.

4.3 Matched Difference-in-Difference Analysis

Even though the FE analysis produces more robust results than a simple OLS analysis, it can be argued that causality can not fully be established, as the FE model cannot remove any time-varying unobserved heterogeneity.

Difference-in-difference (DiD) estimation is able to capture both time-invariant and time-varying confounders (Wooldridge, 2012). Calculating the first difference between before and after outcomes in the treatment group controls for time-invariant factors within the treated group. Subtracting the second difference, that is the before and after difference in outcomes of the control group, from the first difference controls for time-varying factors (Wooldridge, 2012). Given the common trend assumption, stating that in the absence of any treatment, the difference between control and treated group should be constant over time, holds, the final difference-in-difference in outcomes can be interpreted as the causal effect of the treatment on the outcome (Wooldridge, 2012).

To apply the DiD model to the data, round 4 is defined as the post-treatment period, whereas rounds 2 and 3 serve as pre-treatment periods to establish if the common trend assumption holds. Consequently, the sample is restricted to only those individuals that are present in all three rounds and that do not experience any type of shock in the two pre-treatment periods[6]. This also means, that the restricted sample only consists of children from the younger cohort, as older cohort children are not part of the sample in period 4. Thus, the sample size is greatly reduced.

To estimate the parameter of interest, FE estimators are used instead of OLS estimators. This is motivated by work by Lechner et al. (2015) who state that even though FE estimators are numerically equivalent to OLS estimators when used on a balanced panel, which is the case here, only FE estimators and not OLS estimators are consistent if the common trend assumption is affected by selection. This can be assumed to be the case here, as the selection into being treated or not is likely related to pre-treatment characteristics that simultaneously lead to treated and non-treated individuals differing systematically even before treatment.

The corresponding DiD model takes on the following form

$$Y_{it} = \beta_0 + \beta_1 Treated_i + \beta_2 Post_t + \beta_3 PostxTreated_{it} + otherControls_{it} + u_{it} \quad (4.5)$$

[6]Since many children were not present throughout all four rounds or experienced a shock in at least one of the first three rounds, the pre-treatment period is limited to only two periods in order to keep the sample as big as possible

Y_{it} denotes the outcome, *Treated* is a dummy taking on the value 1 if the child experienced a shock in the post-treatment period and 0 otherwise, and *Post* is a dummy for the post-treatment period. β_3 is the parameter of interest capturing the Average Treatment Effect on the Treated (ATT). Other controls include the same controls as described in section 4.1, excluding the controls for age and rounds due to multicollinearity and the controls for ethnicity, religion and school availability due to time-invariance. In addition, note that due to the treatment variable being constant over the two periods, it can only be reported within the interaction term *Post * Treated*. As in the models described earlier, standard errors are clustered at the community or child level for community and individual shocks respectively (see Bertrand et al. (2004) for a discussion of why clustering is important in the DiD framework).

Unfortunately, constructing pre-treatment trends based on the outcomes in rounds 2 and 3 concludes that the common trend assumption does not hold (see Table A.4). In particular, children that experience a community shock in round 4 already increased their hours spent on work or chores significantly more between rounds 2 and 3 than children that would not experience a shock in round 4.

Matching procedures can be used to create a control group that is comparable to the treated group with regard to observed characteristics, making it more likely that the common trend assumption holds. The matched DiD method[7], i.e. running a DiD estimation on a matched sample, goes back to Heckman et al. (1997). I use propensity score matching (PSM) as developed by Rosenbaum and Rubin (1983) to match similar treated and untreated individuals. This technique assigns estimated probabilities of treatment to each individual based on the individual's observed characteristics. This has the advantage that matching does not have to be performed based on a large number of different characteristics, but only based on one parameter, that is the propensity score.

For the matched DiD model to yield unbiased results two additional identifying assumptions exist. Firstly, the conditional independence assumption states that outcomes are independent of the treatment assignment conditional on the propensity score (Rosenbaum and Rubin, 1983). This means that there are no unobserved variables affecting both the outcome and the treatment. Note that the DiD model controls for all time-invariant unobservables, so that only time-varying unobservables could potentially interfere with this assumption. Secondly, the treated and control groups must have an area of common support where propensity score distributions overlap (Heckman et al., 1997).

Using PSM requires certain parameter choices. Firstly, it must be chosen which covariates to include in the propensity score model. The choice of covariates used for the estimation of the propensity score must be selected such that the assumption of conditional independence is satisfied. To make sure that this is the case, the following two points should be considered. On one hand, overparameterizing the model by including insignificant covariates is undesirable, as it may reduce the area of common support (Bryson et al., 2002). On the other hand, resulting estimates might be biased if important covariates are left out of the model (Heckman et al., 1997). Following Caliendo and Kopeinig (2008), I therefore exclude covariates only if they are insignificant and do not increase the regression fit. For the analysis of community shocks, the wealth index, the amount of land owned, a dummy for owning

[7]For a treatise similar to the following, refer to my first master thesis (Pieper, 2022).

any animals, rural/urban area and the availability of schools, the education and gender of the caregiver, the household size and the region are included in the model that estimates the propensity score. The financial access, income diversification and food security situation of the household as well as the child's health and religion are excluded in the propensity score model, as they are not significant in explaining the probability of receiving a shock and do not improve or even worsen the regression fit. For the individual shock, the amount of land owned, a dummy for owning any animals, rural/urban area and for financial access, the child's health and religion, the food security situation and income diversification of the household, and the region are included in the propensity score model. The wealth index, a dummy for owning any animals, the availability of schools, the household size and the gender and education of the caregiver are excluded. The models are estimated using a logit likelihood estimation and the Stata command kmatch written by Jann (2017).

Secondly, Kernel matching is chosen as a matching algorithm. In this case, the matched sample is constructed from weighted averages of all observations in the control group within a caliper[8]. Untreated individuals whose propensity score deviates greatly from the estimated propensity of treated individuals are assigned a small weight, while untreated individuals who have propensity scores similar to those of treated individuals are assigned a higher weight. Kernel matching produces a lower variance than other matching algorithms, especially those that match observations one on one (e.g. nearest neighbor matching), as less observations are dropped (Caliendo and Kopeinig, 2008). Another advantage of Kernel matching over one-on-one matching algorithms is the fact that the problem of the propensity score paradox is reduced. This paradox describes that decreasing the caliper size leads to more balanced matched samples but that the balance decreases at the same time as more observations are discarded for having propensity scores outside of the caliper (King and Nielsen, 2019). One disadvantage of Kernel matching is, that observations that are poor matches could be included in the matched sample (Caliendo and Kopeinig, 2008). To reduce this problem the matched sample is restricted to only observations with common support.

Lastly, when using Kernel matching, a bandwidth has to be selected. While a higher bandwidth leads to a smoother estimated density function and thus a smaller variance, a smaller bandwidth models the features of the true underlying density function better and thus leads to possibly less biased estimates (Caliendo and Kopeinig, 2008). The data-driven automatic bandwidth selection provided by stata selects a bandwidth that yields a compromise between low variance and unbiased estimates (see Jann (2017) for more details).

Figures A.5 and A.6 reflect the matching results by depicting the standard mean differences of the matching covariates for the treated and control groups before and after matching. As can be seen, the covariates of both groups are more balanced after matching, as standard mean differences are closer to zero. To see if balancing the matching covariates solved the problem of different pre-treatment trends, table A.5 shows the difference in pre-treatment outcome trends between treated and untreated individuals for the matched sample. The differences are insignificant, hence the common trend assumption holds.

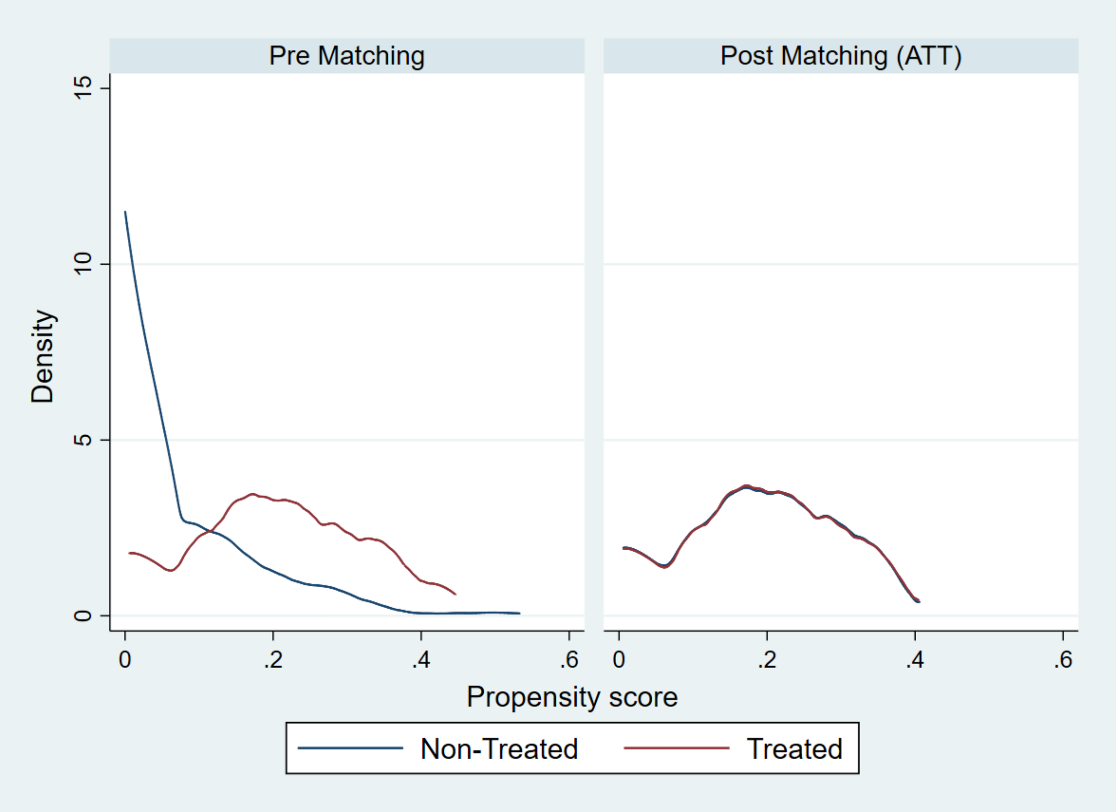
Before using the matched sample, it should be examined how the matched sam-

[8]The word caliper refers to a specific tolerance level regarding the maximum propensity score distance (Caliendo and Kopeinig, 2008).

ple differs from the original sample. Figures 4.1 and 4.2 depict the Kernel density of the propensity scores before and after the matching process. The figures show the area of common support, i.e. the area where the density of the treated (red line) and non-treated (blue line) individuals overlap and demonstrate visually that the common support assumption holds. In the case of community shocks, 85 observations, of which 2 are treated individuals, have propensity scores outside of the common support and are thus not included in the matched sample. In the case of individual shocks, this applies to 15 observations, of which 10 are treated individuals. In total, 462 observations can be used for the analysis of community shocks, and 480 for the analysis of individual shocks. Figures A.3 and A.4 show the density of the propensity scores of the total (blue line), matched (green line) and unmatched (red) sample (i.e. the observations that were dropped due to lack of common support). The matched sample is still representative of the total sample as both propensity score densities are very similar.

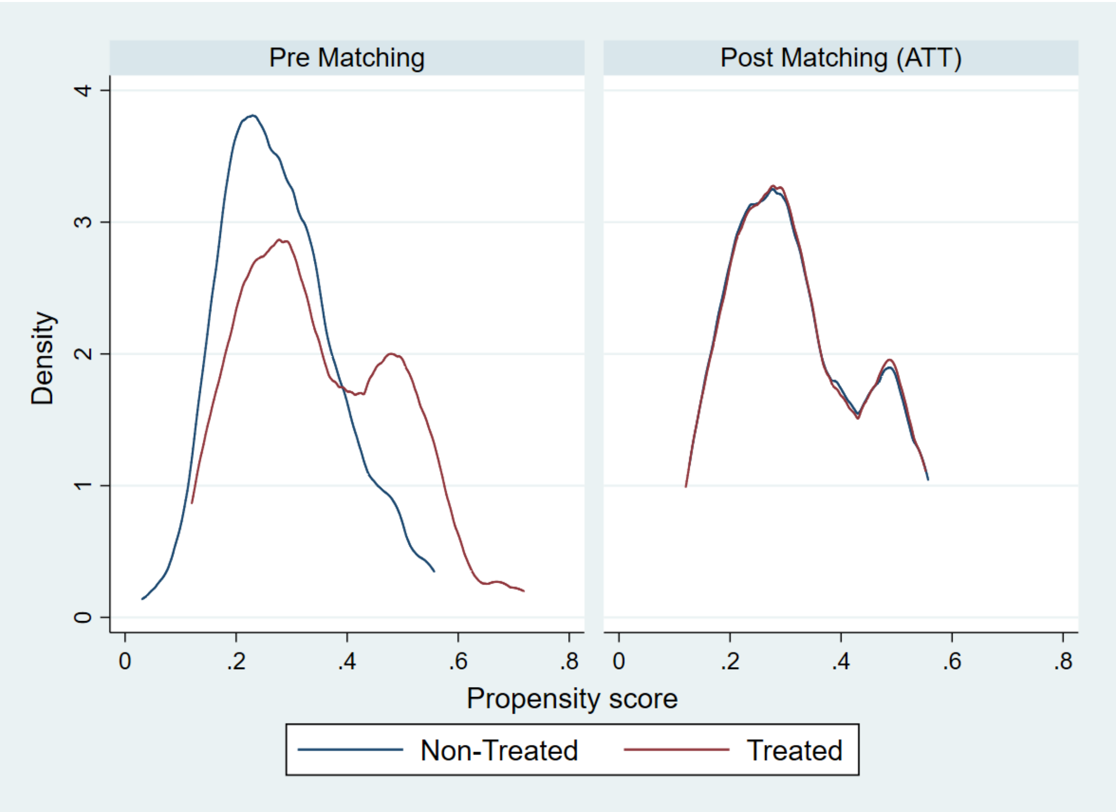
All in all, the DiD specification is ideal in terms of establishing causality. However, the sample is greatly reduced to only 462 observations in the community shock analysis and 480 observations in the individual shock analysis, of which only a fraction are treated individuals. Additionally, given the survey design, the DiD setup reduces the variation in age, so that results are only representative for children that are 12 years old in the post-treatment period. Therefore, the FE model is the preferred model. It might be biased, however, as explained above, potentially negatively, so that the reported results are conservative estimates. In addition, and as will be shown below, OLS and DiD results point to the same direction as results obtained from the FE analysis, affirming the reliability of the results.

Figure 4.1: Community Shock: Kernel density of the propensity scores



Note: Graph depicts the Kernel density of the propensity scores pre and post matching.
Source: Own calculations based on YL rounds 2-4 and Rounds 1-5 Constructed Files.

Figure 4.2: Individual Shock: Kernel density of the propensity scores



Note: Graph depicts the Kernel density of the propensity scores pre and post matching.
Source: Own calculations based on YL rounds 2-4 and Rounds 1-5 Constructed Files.

5

Empirical Analysis

5.1 Main Results

The main results are reported in Tables 5.1 to 5.4. While the first three columns report the OLS estimates including more controls for every specification, the fourth column reports the FE estimates and the fifth column reports the DiD estimates. As justified above, the FE estimates are the preferred results.

As shown in Table 5.1, the OLS results suggest that children that experience a community shock work significantly more hours than those that do not. This can be confirmed in the FE analysis. In fact, according to the FE estimates children that experience a community shock work on average 0.16 hours per day more than other children. The same pattern, even though with slightly smaller coefficients also arises from the analysis of individual shocks on working hours (see Table 5.2). Children hit by such a shock work significantly more hours on average, 0.12 hours per day to be precise, than children who do not experience an individual shock. To assess whether the shock effects are economically and not just statistically significant, I consider the average number of hours of work provided by children (see Table 3.1). Children provide on average 1.5 hours per day. Relative to this, an average increase of 0.16 hours per day constitutes a considerable change. To further put the importance of the effect of shocks into perspective, I examine the magnitude of other controls. The FE estimates from both tables 5.1 and 5.2 suggest that experiencing an increase in the wealth index of 0.2, which is the minimum increase needed to switching from the category "poorest" to "less poor", decreases the hours of work provided by a child by 0.04 hours per day ceteris paribus[1]. At the same time, children in rural areas work on average 0.49 hours per day more than urban children. The age makes an even bigger difference in the time children spent on work when other factors stay equal. For example, children aged eight work on average about 1.3 hours more per day than children aged five. Moreover, both the availability of schools and the ownership of productive assets are identified by the literature as important child labor determinants (e.g. Basu et al. (2010) and Dammert et al. (2018)). My results suggest that the lack of access to schools increases the time children spent on work by on average 1.47 hours per day. Further, while the ownership of animals increases the average time spent working by about 0.2 hours per day, the ownership of land does not lead to any change in child labor ceteris paribus (see table A.6 which depicts the complete regression output of the FE regression of community and individual

[1] 0.2 multiplied by the estimated coefficient of the wealth index.

shocks on working hours). Comparing these magnitudes shows that while shocks are not the most important factors determining the amount of work provided by children, the magnitude of their effects on children's work hours is comparatively important.

Tables 5.3 and 5.4 depict the effect of shocks on hours spent on chores. Contrary to above, no robust effect on the hours spent on chores can be detected. While the OLS estimates suggest significant effects of experiencing an individual shock on hours spent on chores, the FE analysis can not confirm this (see Table 5.4). In fact, the in the FE model estimated magnitude of the effect is below 0.05 hours per day. Further, neither OLS nor FE estimates suggest a significant effect of community shocks on children's hours spent on chores (see Table 5.3). Here, the direction of the coefficients even points towards a reduction in hours, namely by 0.07 hours per day, even though the effect is insignificant.

The pattern of these results allows for the following interpretation. While children increase their hours spent working when the household is hit by a shock, they do not significantly adapt their hours spent on chores. This suggests that the household relies on the economic support of their children in order to mitigate the negative consequences of a shock. This is particularly pronounced in the case of community shocks, where households might be less able to rely on other support, as surrounding households are also hit by a shock. The finding that the effect of shocks on hours spent on chores is negative, albeit insignificant, points towards an adaptive behavior, where children reallocate time from chores to work.

Results from the matched DiD model require a more thorough interpretation (see column 5 in Tables 5.1-5.4). Consistent with the results from the OLS and FE specification, children's hours spent on chores are not found to be significantly altered by experiencing a community or an individual shock (see Table 5.3 and 5.4). Again, the insignificant coefficients of the causal effect on chores enter negatively into the model, so that the above mentioned suggestion of a reallocation of time spent on chores to time spent on work is supported. However, in contrast to the OLS and FE results, the DiD model indicates a significant increase in children's hours spent on work only when they are affected by a community shock (see Table 5.1), but not when they are affected by an individual shock (see Table 5.2). The heterogeneity analysis in section 5.2 helps to explain why the DiD results do not confirm that children significantly increase their hours spent on work after experiencing an individual shock. Note, that all children in the post-treatment period are 12 years of age. As will be shown in Table 5.6, 12-year-olds that are hit by an individual shock increase their hours spent on work less than 8-year-olds and significantly less than 5-year-olds in the same situation. Only using a sample of 12-year-olds in the post-treatment period thus leads to muted results, explaining why the measured causal effect is insignificant. Following the same logic, it is also not surprising that the causal effect of community shocks on hours worked measured by the DiD model is more significant (10% in the FE analysis, 1% in the DiD analysis) and bigger in magnitude than the FE results. 12-year-olds increase their hours spent on work more than 15- and 8-year-olds and significantly more than 5-year-olds so that the causal effect in the DiD sample is more pronounced.

To conclude, given the limited sample that can be used for the DiD analysis, results should be interpreted with caution. Nevertheless, the fact that the results from this analysis appear consistent with the results from the FE analysis in the context of an age-restricted sample is suggestive that experiencing shocks significantly alters children's time spent on work.

Table 5.1: Regression: Community Shock and Hours work

	OLS	OLS	OLS	FE	DiD
Community Shock	1.216***	1.225***	0.425***	0.159*	
	(0.210)	(0.199)	(0.0978)	(0.0876)	
Post					-0.477**
					(0.225)
Post * Treated					0.823***
					(0.289)
Age 8		1.066**	0.999***	1.239***	
		(0.447)	(0.339)	(0.200)	
Age 12		1.267***	1.290***	1.498***	
		(0.145)	(0.140)	(0.247)	
Age 15		1.167***	1.186***	1.532***	
		(0.399)	(0.309)	(0.193)	
Male		1.529***	1.544***		
		(0.181)	(0.177)		
Wealth Index			-1.524***	-0.194	0.497
			(0.304)	(0.330)	(1.074)
Rural			0.585***	0.488**	2.138***
			(0.182)	(0.195)	(0.654)
Constant	1.365***	-1.161	0.637	1.239*	1.959
	(0.179)	(0.815)	(0.864)	(0.730)	(1.401)
Round Controls	Yes	Yes	Yes	Yes	No
Personal Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
N	7220	7220	7220	7220	376
R^2	0.073	0.201	0.295	0.093	0.194

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Baseline category for age: Age 5. Round controls: dummies for study round 2-4 (baseline category Round 5). Personal controls: dummy for being the oldest child in the household (HH) and the child's relation to the HH head, the child's religion and ethnicity. HH controls: the region, the amount of land owned by the HH, dummies for owning any livestock, for the availability of schools, the education of caregiver, the gender of the caregiver, and the HH size. In the FE specification, dummies for rounds 2 and 4 as well as the children's gender, ethnicity and religion are excluded. In the DiD specification, the child's age, ethnicity and religion as well as the dummy for the availability of schools are excluded.
Robust standard errors clustered at the community level in parentheses
Source: Own calculations based on Young Lives rounds 2-5 (OLS and FE) or rounds 2-4 (DiD) and Rounds 1-5 Constructed Files.

Table 5.2: Regression: Individual Shock and Hours work

	OLS	OLS	OLS	FE	DiD
Individual Shock	0.0661	0.0878	0.123**	0.115*	
	(0.0592)	(0.0546)	(0.0488)	(0.0596)	
Post					0.338
					(0.320)
Post * Treated					0.507
					(0.476)
Age 8		0.526***	0.835***	1.303***	
		(0.170)	(0.165)	(0.148)	
Age 12		1.277***	1.288***	1.421***	
		(0.0993)	(0.0950)	(0.0936)	
Age 15		0.636***	1.031***	1.527***	
		(0.192)	(0.184)	(0.0988)	
Male		1.515***	1.538***		
		(0.0625)	(0.0524)		
Wealth Index			-1.641***	-0.211	-2.115
			(0.201)	(0.341)	(2.008)
Rural			0.673***	0.493**	0.269
			(0.0822)	(0.244)	(0.693)
Constant	1.763***	-0.0515	1.195*	1.817***	3.648**
	(0.0608)	(0.310)	(0.639)	(0.548)	(1.775)
Round Controls	Yes	Yes	Yes	Yes	No
Personal Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
N	7220	7220	7220	7220	438
R^2	0.009	0.137	0.290	0.091	0.130

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Baseline category for age: Age 5. Round controls: dummies for study round 2-4 (baseline category Round 5). Personal controls: dummy for being the oldest child in the HH and the child's relation to the HH head, the child's religion and ethnicity. HH controls: the region, the amount of land owned by the HH, dummies for owning any livestock, for the availability of schools, the education of caregiver and the HH size. In the FE specification, dummies for rounds 2 and 4 as well as the children's gender, ethnicity and religion are excluded. In the DiD specification, the child's age, ethnicity and religion as well as the dummy for the availability of schools are excluded.
Robust standard errors clustered at the child level in parentheses
Source: Own calculations based on Young Lives rounds 2-5 (OLS and FE) or rounds 2-4 (DiD) and Rounds 1-5 Constructed Files.

Table 5.3: Regression: Community Shock and Hours chores

	OLS	OLS	OLS	FE	DiD
Community Shock	0.129	0.0988*	-0.156	-0.0658	
	(0.168)	(0.147)	(0.0899)	(0.0689)	
Post					0.293
					(0.483)
Post * Treated					-0.485
					(0.293)
Age 8		-0.192	-0.0988	0.978***	
		(0.586)	(0.592)	(0.207)	
Age 12		1.464***	1.463***	1.225***	
		(0.176)	(0.178)	(0.225)	
Age 15		0.517	0.633	1.514***	
		(0.570)	(0.559)	(0.233)	
Male		-1.490***	-1.486***		
		(0.0963)	(0.0952)		
Wealth Index			-0.416	-0.0683	-3.509**
			(0.337)	(0.469)	(1.695)
Rural			0.606**	0.0887	-1.157*
			(0.295)	(0.191)	(0.666)
Constant	2.698***	3.425***	4.227***	2.277***	5.459***
	(0.150)	(1.189)	(1.168)	(0.641)	(1.278)
Round Controls	Yes	Yes	Yes	Yes	No
Personal Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
N	7220	7220	7220	7220	376
R^2	0.023	0.233	0.256	0.126	0.207

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Baseline category for age: Age 5. Round controls: dummies for study round 2-4 (baseline category Round 5). Personal controls: dummy for being the oldest child in the HH and the child's relation to the HH head, the child's religion and ethnicity. HH controls: the region, the amount of land owned by the HH, dummies for owning any livestock, for the availability of schools, the education of caregiver, the gender of the caregiver, and the HH size. In the FE specification, dummies for rounds 2 and 4 as well as the children's gender, ethnicity and religion are excluded. In the DiD specification, the child's age, ethnicity and religion as well as the dummy for the availability of schools are excluded.
FE estimation. Robust standard errors clustered at the community level in parentheses.
Source: Own calculations based on Young Lives rounds 2-5 (OLS and FE) or rounds 2-4 (DiD) and Rounds 1-5 Constructed Files.

Table 5.4: Regression: Individual Shock and Hours chores

	OLS	OLS	OLS	FE	DiD
Individual Shock	0.214***	0.176***	0.179***	0.0456	
	(0.0496)	(0.0436)	(0.0429)	(0.0526)	
Post					-0.194
					(0.251)
Post * Treated					-0.267
					(0.353)
Age 8		-0.285*	-0.145	0.970***	
		(0.155)	(0.155)	(0.130)	
Age 12		1.464***	1.469***	1.263***	
		(0.0918)	(0.0914)	(0.0878)	
Age 15		0.428**	0.594***	1.542***	
		(0.166)	(0.165)	(0.0940)	
Male		-1.491***	-1.481***		
		(0.0463)	(0.0454)		
Wealth Index			-0.377**	-0.0713	1.000
			(0.170)	(0.310)	(2.105)
Rural			0.592***	0.0872	-0.488
			(0.0729)	(0.214)	(0.647)
Constant	2.691***	3.450***	3.536***	2.104***	6.373***
	(0.0435)	(0.265)	(0.433)	(0.477)	(1.642)
Round Controls	Yes	Yes	Yes	Yes	No
Personal Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
N	7220	7220	7220	7220	438
R^2	0.025	0.235	0.255	0.126	0.018

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Baseline category for age: Age 5. Round controls: dummies for study round 2-4 (baseline category Round 5). Personal controls: dummy for being the oldest child in the HH and the child's relation to the HH head, the child's religion and ethnicity. HH controls: the region, the amount of land owned by the HH, dummies for owning any livestock, for the availability of schools, the education of caregiver and the HH size. In the FE specification, dummies for rounds 2 and 4 as well as the children's gender, ethnicity and religion are excluded. In the DiD specification, the child's age, ethnicity and religion as well as the dummy for the availability of schools are excluded.
FE estimation. Robust standard errors clustered at the child level in parentheses.
Source: Own calculations based on Young Lives rounds 2-5 (OLS and FE) or rounds 2-4 (DiD) and Rounds 1-5 Constructed Files.

5.2 Effect Heterogeneity

To analyze any heterogeneity in the effect of shocks on children's time use, interaction terms of the shock variable with the corresponding characteristics are used. This takes on the following form:

$$Y_{\text{it}} = \beta_1 + \beta_2 Shock_{it} + \beta_3 Shock_{it} * C_{it} + \beta_4 C_{it} + \beta_5 Personal_{it} + \beta_6 Household_{it} + a_i + u_{it} \tag{5.1}$$

Household and personal controls are equivalent to the ones described in section 4.1, while C stands for the characteristics that are expected to generate heterogeneous treatment effects. Specifically, they are a dummy for gender, a vector of age dummies for ages 8, 12 and 15 with age 5 as the omitted category, a dummy for being a rural as opposed to an urban household and the wealth index.

The results of the regressions can be found in Tables 5.5 and 5.6. Surprisingly, the heterogeneity in the effect according to gender is not significant. This result could indicate that households override gender roles in extreme situations, as assistance is needed from as many household members as possible, and thus from daughters as well as sons. It could however also be related to the nature of the data. Comparing children within a household, which is not possible with the data at hand as the survey only interviews the Young Lives child but not the other children in the household, could potentially lead to gendered outcomes.

Heterogeneous effects according to age adhere to the following pattern: When hit with a community shock, 8-year-olds and 12-year-olds increase their working hours significantly more than 5-year-olds, with 12-year-olds showing the biggest increase. In fact, 12-year-olds that experience a community shock increase their working hours on average by 0.8 hours per day more than 5-year-olds. This is in line with hypothesis that older children increase their time spent on work and chores more than younger children when hit by a shock. Deviating from the hypothesis, 15-year-olds do not increase their hours spent on work significantly more than 5-year-olds. One possible explanation for this could be that 15-year-olds already provide more working hours than any other age group on average so that they have less "room" to increase their work time than younger children that provide fewer work hours in the first place. While the hypothesis that older children increase their time burden more than younger children is partly confirmed for the effect of community shocks on working hours, it is not confirmed for the effect of community shocks on chores. Here, 5-year-olds increase their hours the most, with children increasing their hours spent on chores by less and less the older they get. Specifically, 15-year-olds increase their hours spent on chores by on average 0.56 hours per day less than 5-year-olds. The same pattern, that is 5-year-olds increasing their time the most, can also be seen in the analysis of the effect of individual shocks on both work and chores, even though less pronounced. This could again be due to the fact that older children already provide more work and chores before any shock so that the subsequent increases are not as significant.

As expected, children from households that score higher on the wealth index increase their hours spent on chores significantly less than poorer children, both in the case of community and individual shocks. There is no significant difference in the effect on working hours. The same pattern is visible for rural/urban being the heterogeneous characteristic. Expectedly, children from rural households increase their hours spent on chores more than urban children. The difference of the effect on working hours for rural and urban children is not significant. The finding that the heterogeneity due to wealth and rural status are not significant in the case of working hours could be linked to the availability of work. The hypotheses that rural and poorer households have a greater need for the support of their children in the event of a shock than urban and richer households are based on household labor supply. However, despite the level of labor supply preferred by the household, the demand for labor, or in other words the opportunities to work, might be limited for poorer and rural households. This could be the case for paid jobs outside the household but also for work provided within family businesses, for example due to limited margins to extend a business in poorer areas, or on family farms where the labor needed is limited by the size of the farm and would require investments to be extended. Hence, if labor demand is limited for rural and poorer households, children from such households might not increase their work time in the event of a shock more than children from richer and urban households simply because there is no work available to them.

Table 5.5: Heterogeneous effects: Community shock

	Work	Work	Work	Work	Chores	Chores	Chores	Chores
Community Shock	0.153*	-0.392	-0.0465	0.293	-0.0524	0.305*	0.255*	-0.336***
	(0.0873)	(0.324)	(0.233)	(0.192)	(0.110)	(0.167)	(0.147)	(0.110)
Male*Comm. Shock	0.0102				-0.0247			
	(0.118)				(0.128)			
Age 8*Comm. Shock		0.605*				-0.317		
		(0.348)				(0.199)		
Age 12*Comm. Shock		0.802**				-0.399**		
		(0.388)				(0.171)		
Age 15*Comm. Shock		0.529				-0.564***		
		(0.349)				(0.191)		
Wealth Index*Comm. Shock			0.709				-1.106***	
			(0.646)				(0.367)	
Rural*Comm. Shock				-0.152				0.305**
				(0.212)				(0.126)
Constant	1.240*	1.643***	1.366**	1.180	2.274***	1.998***	2.079***	2.396***
	(0.736)	(0.595)	(0.645)	(0.743)	(0.648)	(0.680)	(0.651)	(0.634)
Personal and Household Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7220	7220	7220	7220	7220	7220	7220	7220
R^2	0.093	0.098	0.094	0.093	0.126	0.129	0.128	0.126

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ **Note:** Personal and HH controls: dummies for age 8, 12 and 15 (baseline category: Age 5), for survey round 3 (baseline category round 4) and for being the oldest child in the HH and the child's relation to the HH head, the region, wealth index, the amount of land owned by the HH, dummies for owning any livestock, for rural/urban HH and for the availability of schools, the education of caregiver, the gender of the caregiver, and the HH size. FE estimation. Robust standard errors clustered at community level in parentheses. **Source:** Own calculations based on Young Lives rounds 2-5 and Rounds 1-5 Constructed Files.

Table 5.6: Heterogeneous effects: Individual shock

	Work	Work	Work	Work	Chores	Chores	Chores	Chores
Individual Shock	0.207***	0.380**	0.0972	0.0158	-0.0369	0.208	0.276***	-0.151
	(0.0743)	(0.152)	(0.134)	(0.0875)	(0.0797)	(0.147)	(0.106)	(0.0922)
Male*Ind. Shock	-0.171				0.154			
	(0.114)				(0.103)			
Age 8*Ind. Shock		-0.148				-0.171		
		(0.180)				(0.175)		
Age 12*Ind. Shock		-0.359**				-0.126		
		(0.176)				(0.167)		
Age 15*Ind. Shock		-0.429**				-0.297*		
		(0.182)				(0.170)		
Wealth Index*Ind. Shock			0.0559				-0.727***	
			(0.308)				(0.265)	
Rural*Ind. Shock				0.127				0.251**
				(0.110)				(0.108)
Constant	1.839***	1.723***	1.827***	1.842***	2.085***	2.026***	1.982***	2.153***
	(0.548)	(0.553)	(0.549)	(0.549)	(0.478)	(0.483)	(0.482)	(0.476)
Personal and Household Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7220	7220	7220	7220	7220	7220	7220	7220
R^2	0.092	0.093	0.091	0.092	0.126	0.126	0.127	0.126

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ **Note:** Personal controls: dummies for age 8, 12 and 15 (baseline category: Age 5), for survey round 3 (baseline category round 4) and for being the oldest child in the HH and the child's relation to the HH head. HH controls: the region, wealth index, the amount of land owned by the HH, dummies for owning any livestock, for rural/urban HH and for the availability of schools, the education of caregiver and the HH size. FE estimation. Robust standard errors clustered at child level in parentheses. **Source:** Own calculations based on Young Lives rounds 2-5 and Rounds 1-5 Constructed Files.

5.3 Extensions

5.3.1 Mitigation Channels

Having established that children adapt their time spent on work and chores after experiencing a shock, I will take a look at the possible mitigation channels identified from the literature. To do so, the FE model with interaction terms (see equation 5.1) is modified to:

$$Y_{\text{it}} = \beta_1 + \beta_2 Shock_{it} + \beta_3 Shock_{it} * M_{it} + \beta_4 M_{it} + \beta_5 Personal_{it} + \beta_6 Household_{it} + a_i + u_{it} \tag{5.2}$$

For a description of household and personal controls, see chapter 4 and the table notes of Tables 5.7 to 5.9. M stands for the different mitigation channels, namely *Social Networks, Financial Access* and *Income Diversification*. The analysis of social networks and financial access as possible mitigation channels is performed on the full sample excluding individuals that have no observations for the newly added mitigation variable, while the analysis of the income diversification as a mitigation channel is carried out on a sample excluding observations from round 5. This reduces the sample to 5470 observations. Results for the three channels are depicted in Tables 5.7 to 5.9, where the interaction terms between mitigation channel and shocks provide the coefficients of interest.

Firstly, the interaction term of social networks and community shock enters the model negatively, indicating that children who live in households that have more people to rely on in times of need increase their hours spent on chores or work by less when hit by a shock than children from less socially integrated households (see Table 5.7). The difference in effect between children from better and worse socially integrated households is significant for changes in hours spent on chores. The pattern of results is in line with the hypothesis posed in section 2.2.

Secondly, children with financial access, that is children from households that are situated in a community that has access to credit or finance through public banks, private banks, local government credit, agricultural cooperative societies or microfinance institutions, do not react significantly different to community shocks than children from households without financial access, nor does their increase in hours spent on work differ significantly when hit by an individual shock (see Table 5.8). The mitigation effect is only significant for the hours spent on chores after experiencing an individual shock. In that case, children from households with financial access increase their hours spent on chores by less than children from other households. The finding that the mitigation channel seems to have no significant effect on hours spent on work nor on chores if a community shock occurs could mean that the mitigation effect of financial access is not strong. However, the lack of significance may be more attributable to the way the variable *Financial Access* is defined. Since it is only asked whether the community generally has access to finance, not whether each household can also benefit from it, a high proportion of children, ranging from 84% to 100% in each round, are classified as having financial access. In reality, many households might not be able to receive credit if they are too poor to qualify or discriminated against based on gender, ethnicity or other characteristics. A more precise measure for financial access would thus benefit further investigations of this mitigation channel.

Lastly, the number of sources of income of the household seems not to play any significant role in mitigating the effect of an individual shock on children's hours spent on chores or work. There is a significant effect when the child is affected by a community shock. However, where the effect on chores is of the expected sign, indicating that children from households with more income sources increase their hours on chores less than other children affected by a community shock, the sign of the effect on children's work hours is of the opposite sign. Given this counter intuitive results, it should be again referred to the data adequacy as explained in more detail in section 3.2. Specifically the fact that the variable *Income Diversification* is not able to distinguish what labor share of the household is allocated to each activity opens up the possibility of bias due to mismeasurements in the data. Thus, the results concerning the income diversification channel should be interpreted with caution and further research is needed to confirm any mitigating effects.

Table 5.7: Mitigation Channels: Social Networks

	Community Shock		Individual Shock	
	Work	Chores	Work	Chores
Community Shock	0.245**	0.102		
	(0.117)	(0.0918)		
Social Networks*Comm. Shock	-0.0357	-0.0716**		
	(0.0383)	(0.0332)		
Individual Shock			0.160	0.192**
			(0.109)	(0.0946)
Social Networks*Ind. Shock			-0.0260	-0.0715*
			(0.0432)	(0.0368)
Social Networks	-0.00459	0.0448	-0.0135	0.0347
	(0.0303)	(0.0294)	(0.0290)	(0.0226)
Age 8	1.259***	0.967***	1.326***	0.965***
	(0.194)	(0.207)	(0.148)	(0.130)
Age 12	1.520***	1.249***	1.434***	1.280***
	(0.248)	(0.224)	(0.0940)	(0.0884)
Age 15	1.555***	1.530***	1.545***	1.556***
	(0.193)	(0.230)	(0.0997)	(0.0942)
Wealth Index	-0.201	-0.0678	-0.222	-0.0921
	(0.334)	(0.468)	(0.341)	(0.311)
Rural	0.489**	0.108	0.488**	0.0970
	(0.200)	(0.192)	(0.245)	(0.213)
Constant	1.263*	2.223***	1.878***	2.079***
	(0.755)	(0.638)	(0.561)	(0.483)
Personal and Household Controls	Yes	Yes	Yes	Yes
N	7192	7192	7192	7192
R^2	0.095	0.128	0.093	0.128

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The variable *Social Networks* is defined as the number of people a household can rely on in times of financial need (1=1-2 people; 2= 3-5 people, 3=6-10 people, 4=11-15 people, 5=16-20 people, 6=21-30 people, 7=over 30 people). Baseline category for age: age 5. Controls include: dummies for survey round 3 (baseline category round 4) and for being the oldest child in the HH and the child's relation to the HH head, the region, wealth index, the amount of land owned by the HH, dummies for owning any livestock and for the availability of schools, the education and gender (excluded in columns 3 and 4) of the caregiver and the HH size. FE estimation. Robust standard errors clustered at community (community shocks) or child (individual shocks) level in parentheses.

Source: Own calculations based on Young Lives rounds 2-5 and Rounds 1-5 Constructed Files.

Table 5.8: *Mitigation Channels: Financial Access*

	Community Shock		Individual Shock	
	Work	Chores	Work	Chores
Community Shock	-0.0592	0.332		
	(0.169)	(0.268)		
Financial Access*Comm. Shock	0.202	-0.255		
	(0.199)	(0.273)		
Individual Shock			0.214	0.394**
			(0.183)	(0.165)
Financial Access*Ind. Shock			-0.0721	-0.390**
			(0.194)	(0.173)
Financial Access	-0.0435	-0.246	0.156	-0.146
	(0.0800)	(0.333)	(0.142)	(0.133)
Age 8	1.319***	0.895***	1.407***	0.883***
	(0.237)	(0.242)	(0.159)	(0.139)
Age 12	1.410***	1.459***	1.332***	1.427***
	(0.250)	(0.242)	(0.102)	(0.0940)
Age 15	1.528***	1.610***	1.544***	1.588***
	(0.195)	(0.248)	(0.110)	(0.105)
Wealth Index	0.386	-0.584	0.317	-0.556
	(0.427)	(0.467)	(0.378)	(0.356)
Rural	1.332***	-0.796***	1.280***	-0.855*
	(0.376)	(0.236)	(0.417)	(0.453)
Constant	0.461	3.722***	1.058	3.769***
	(1.113)	(0.828)	(1.245)	(0.741)
Personal and Household Controls	Yes	Yes	Yes	Yes
N	6082	6082	6082	6082
R^2	0.110	0.145	0.109	0.145

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The variable *Financial Access* is a dummy taking on the value 1 if the household is situated in a community that has access to credit or finance through public banks, private banks, local government credit, agricultural cooperative societies or microfinance institutions, and 0 otherwise. Baseline category for age: age 5. Controls include: dummies for survey round 3 (baseline category round 4) and for being the oldest child in the HH and the child's relation to the HH head, the region, wealth index, the amount of land owned by the HH, dummies for owning any livestock and for the availability of schools, the education and gender (excluded in columns 3 and 4) of the caregiver and the HH size. FE estimation. Robust standard errors clustered at community (community shocks) or child (individual shocks) level in parentheses.
Source: Own calculations based on Young Lives rounds 2-5 and Rounds 1-5 Constructed Files.

Table 5.9: Mitigation Channels: Income Diversification

	Community Shock Work	Community Shock Chores	Individual Shock Work	Individual Shock Chores
Community Shock	-0.0455	0.260*		
	(0.133)	(0.141)		
Income Diversification*Comm. Shock	0.0441*	-0.0699***		
	(0.0232)	(0.0203)		
Individual Shock			0.131	0.107
			(0.107)	(0.0981)
Income Diversification*Ind. Shock			0.00504	-0.0125
			(0.0213)	(0.0202)
Income Diversification	0.00499	0.0108	0.0345***	-0.0285**
	(0.0192)	(0.0157)	(0.0131)	(0.0136)
Age 8	1.297***	1.440***	1.284***	1.438***
	(0.214)	(0.222)	(0.0946)	(0.0882)
Age 12	1.436***	1.388***	1.346***	1.410***
	(0.273)	(0.205)	(0.109)	(0.0957)
Age 15	1.568***	2.051***	1.472***	2.079***
	(0.333)	(0.307)	(0.162)	(0.136)
Wealth Index	-0.135	-0.256	-0.192	-0.195
	(0.505)	(0.395)	(0.442)	(0.418)
Rural	0.896***	0.110	0.894***	0.125
	(0.283)	(0.272)	(0.299)	(0.318)
Constant	0.279	2.090***	0.957	2.019***
	(0.897)	(0.709)	(0.632)	(0.579)
Personal and Household Controls	Yes	Yes	Yes	Yes
N	5470	5470	5470	5470
R^2	0.117	0.155	0.114	0.152

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The sample used is restricted to rounds 2-4. The variable *Income Diversification* is defined as the number of different activities any household member earned money from during the last 12 months. Baseline category for age: age 5. Controls include: dummies for for being the oldest child in the HH and the child's relation to the HH head, the region, wealth index, the amount of land owned by the HH, dummies for owning any livestock and for the availability of schools, the education and gender (excluded in columns 3 and 4) of the caregiver and the HH size. FE estimation Robust standard errors clustered at community (community shocks) or child (individual shocks) level in parentheses.

Source: Own calculations based on Young Lives rounds 2-4 and Rounds 1-5 Constructed Files.

5.3.2 Effects Over Time

Finding rather limited evidence for the functioning of mitigation channels raises the question if childhood shocks have a persistent effect that could translate into worse outcomes in adulthood. To analyse this, the standard FE model is used (see Equation 4.4 for the specification). The shock variables are replaced by *Community* $Shock_{t-1}$ and *Individual* $Shock_{t-1}$ respectively. These lagged variables take on the value 1 if the individual experienced a shock in the previous survey round and 0

Table 5.10: Lagged effects of shocks

	Community Shock		Individual Shock	
	Work	Chores	Work	Chores
Community Shock_{t-1}	0.133	-0.0558		
	(0.104)	(0.147)		
Individual Shock_{t-1}			0.144	0.0664
			(0.121)	(0.0928)
Age 12	-0.00110	0.0881	0.486***	-0.155
	(0.0753)	(0.0956)	(0.134)	(0.105)
Age 15	0.271**	0.442***	0.729***	0.158
	(0.119)	(0.130)	(0.158)	(0.114)
Wealth Index	-0.779*	-0.159	-1.321**	0.424
	(0.406)	(0.632)	(0.663)	(0.514)
Rural	0.320	0.304	0.237	-0.264
	(0.266)	(0.250)	(0.425)	(0.324)
Constant	3.806**	4.837***	4.031**	3.854***
	(1.454)	(0.783)	(1.617)	(0.850)
Personal and Household Controls	Yes	Yes	Yes	Yes
N	2854	2854	3143	3143
R^2	0.023	0.053	0.036	0.025

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The sample used is restricted to rounds 3-5 and to individuals who do not experience a community shock (columns 1 and 2) or an individual shock (columns 3 and 4) in the current period. The variable $Shock_{t-1}$ is a dummy taking on the value 1 if the individual experienced a shock in the previous survey round. Controls include: dummies for age 12 and age 15 (baseline category age 8), dummies for being the oldest child in the HH and the child's relation to the HH head, the region, the amount of land owned by the HH, dummies for owning any livestock and for the availability of schools, the education and gender (excluded in columns 3 and 4) of the caregiver and the HH size. FE estimation. Robust standard errors clustered at community (community shocks) or child (individual shocks) level in parentheses.
Source: Own calculations based on Young Lives rounds 2-4 and Rounds 1-5 Constructed Files.

otherwise. An individual from round 3 with $Community\ Shock_{t-1} = 1$ thus states in round 2 that she experienced a community shock. Consequently, only observations from rounds 3 to 5 are included, as no shock information is available for round 1. Additionally, the sample is restricted to individuals that did not experience a community or individual shock in the current survey round. The restriction is necessary, as experiencing a current shock might be correlated with having experienced a shock in the past (specifically relating individual shocks, such as illness and death of a parent) so that any increases in time spent on chores or work can not be causally attributed to the lagged shock variable but rather to the overall vulnerability of the household. The final samples include 2854 observations for the analysis of community shocks and 3143 observations for the analysis of individual shocks.
Results are presented in Table 5.10. Neither the lagged community nor lagged individual shock variable have a significant effect on children's time use. The insignificance of the coefficients for the effect on chores is expected insofar as children affected by either shock do not spend significantly more hours on chores than other children in the concurrent survey round (see Tables 5.3 and 5.4). However, children's work hours were indeed significantly affected by shocks that occurred in the same survey round (see Tables 5.1 and 5.2). The fact that the lagged shock variables have an insignificant effect on children's hours spent on work suggests that after an initial increase in time spent working, children revert to the mean and do not significantly differ from children who did not experience a community or individual shock in the previous round. The effect of shocks on work are thus transitory.

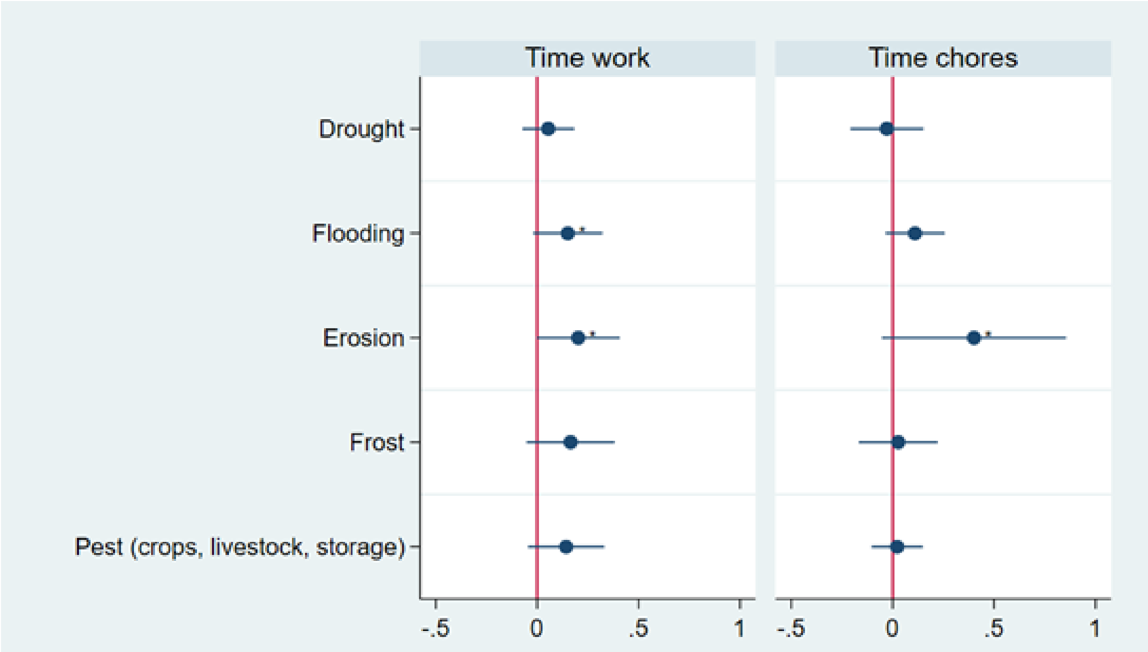
5.3.3 Differentiation of Shocks

Beyond the analysis of mitigation channels and developments over time, one more extension concerning the nature of the shocks is conducted in the following. Grouping individual shocks into two measures, i.e. individual and community shock, could conceal valuable details. Thus, the following analysis differentiates between the different shocks that make up community and individual shocks. The standard FE models (see equation 4.4) are used, replacing the overall community shock variable with variables that indicate experiencing drought, flooding, erosion, frost or pest (on crops, livestock or storage) and the individual shock variable with variables that indicate experiencing theft or destruction of cash, crops, livestock or consumer good, the collapse or fire of a house, the death or illness of father or mother, a separation or the birth of a new household member. Graphs 5.1 and 5.2 illustrate the effect of the different components of the shock variables. Tables A.7 and A.8 in the Appendix provide the coefficients. Note that the results should be interpreted with caution, as the number of treated individuals significantly decreases when separating the different types of individual and community shocks so that the statistical accuracy is affected.

The significant effects of community shocks on the hours children spent on work described in chapter 5 can be attributed to the effect of flooding an erosion. Both shocks significantly increase the hours children spent on work, while drought, frost and pest on crops, livestock or storage do not significantly affect children's work hours (see Table A.7). Graph 5.1 shows that the effect on work is bigger in magnitude than the effect on chores for any community shock with the exception of experiencing and erosion. In that case, children increase their time spent on work by 0.2 hours per day on average while they increase their time spent on chores by 0.4 hours per day on average. Table A.7 confirms that the effect of experiencing an erosion on the hours children spent on chores in the case of a community shock is significant.

Turning to the various individual shocks, the only effect that significantly changes children's hours spent on chores is the arrival of a new baby. On average, children then increase their time spent on chores by 0.32 hours per day. The hypothesis that the illness or death of the mother would affect children's hours spent on chores can not be confirmed. Instead, death and illness of the mother significantly increase children's hours spent on work. The effect of the mother's death is with an average increase of 0.49 hours per day bigger than the effect of the mother's illness, where children increase their time spent on work by on average 0.25 hours per day. It is surprising that the health of the mother, not of the father, results in significant effects. Considering that fathers are often the main provider of the household, the father's wellbeing should be expected to have a bigger impact on children's work than the mother's. It is possible that the result is driven by the lack of children that experienced parental death or illness and the subsequent lack in statistical precision. Further research with more comprehensive data is required to establish how these results should be interpreted.

Figure 5.1: Effect of different community shocks on work and chores

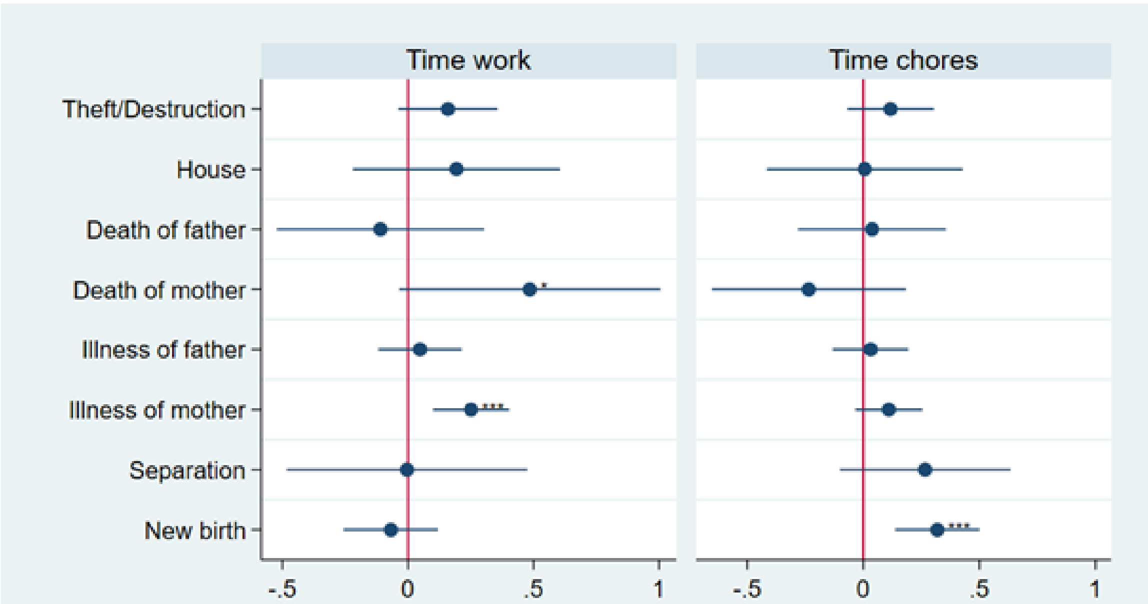


* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Graph depicts point estimates and 95% confidence intervals of the effect of different shock variables on children's hours spent on work and chores. The corresponding table can be found in the Appendix (A.7).

Source: Own calculations based on YL rounds 2-5 and Rounds 1-5 Constructed Files.

Figure 5.2: Effect of different individual shocks on work and chores



* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Graph depicts point estimates and 95% confidence intervals of the effect of different shock variables on children's hours spent on work and chores. The corresponding table can be found in the Appendix (A.7).

Source: Own calculations based on YL rounds 2-5 and Rounds 1-5 Constructed Files.

6

Discussion

The overall aim of this thesis is to analyse if children in Ethiopia adapt their time use when they experience community or individual shocks. It can be confirmed that children significantly increase their time spent on work after experiencing either of the two shocks. Comparing the estimated coefficients with the sample average of children's working hours concludes that the magnitude of the increase is of relative importance. The results are thus generally in line with the prevailing finding in the literature that child labor is determined by negative shocks (Dehejia and Gatti (2002), Duryea et al. (2007), Beegle et al. (2006) and Bandara et al. (2015)) or, from the perspective of the shock literature, that increasing the labor supply of the household by employing children is used to deal with shocks ex-post (see Morduch (1995) and Dercon (2002)). I find children to be more affected by community than by individual shocks. This is conforming to the assessment that risk-sharing mechanisms at the community level are of limited assistance if the whole community is affected by the shock (Dercon, 2002). A look at the estimated coefficients of other factors allows to judge how important shocks are compared to other determinants of child labor reported in the literature. Poverty is thereby named as one of the most important of these determinants (Basu and Van (1998), Edmonds and Pavcnik (2005) and Posso (2020)). The results of my analysis suggest that the impact of shocks on children's work time is bigger in magnitude than that of the socio-economic status of the household. This could however stem from the way the wealth index, that only proxies for poverty, is measured. Moreover, the wealth paradox described by Bhalotra and Heady (2003) and Basu et al. (2010) identifies productive assets as important determinants of child labor as they provide employment opportunities for children. This insight can here only be confirmed for the ownership of animals, not that of land. It can further be concluded that the impact of shocks on children's working hours is of a similar magnitude as the impact of owning animals. Lastly, Edmonds and Pavcnik (2005) and Dammert et al. (2018) mention the availability of schools as child labor determinants. Indeed, my results confirm that this factor has a significant effect on children's hours spent on work. The estimated magnitude of the effect is in fact much larger than that of the effect of shocks. The finding in this analysis that schooling has a comparatively large importance relative to other determinants of child labor, such as shocks, is consistent with the assessment that parents generally prefer to send their children to school rather than to work (Ranjan, 1999).

Contrary to what was hypothesized in section 2.2, the evidence for an increase in hours spent on chores after experiencing a shock is not robust. That predominantly children's work time is affected and not children's time spent on chores points towards income effects playing a more important role than substitution effects in the household bargaining process that determines how children's time use changes following a shock. This is in line with models that define the lack of income as the main determinant of child labor such as Basu and Van (1998), Ranjan (1999) and Bandara et al. (2015).

The hypotheses posed in section 2.2 related to any heterogeneous effects could only partly be confirmed. While differences in age lead to heterogeneous effects of shocks on hours spent on work and chores, differences in the wealth index and the rural/urban status only heterogeneously affect children's hours spent on chores. Gender does not lead to any heterogeneous effect. Relating some of these results to the literature offers further insights. To begin with, the lack of a gendered result stands out as contradictory to the literature (see e.g. Dammert et al. (2018)). This could potentially be due to households ignoring gender roles when reacting to shocks or due to the fact that the data of the Young Lives survey was acquired in a way that does not allow for a comparison between children within one household. A different data set might thus be useful to confirm the findings in the literature. Furthermore, while I confirm that poorer and rural children increase their hours spent on chores significantly more than richer children when affected by a shock, they increase their hours spent on work less than richer and urban children, although insignificantly so. This could be interpreted as an indicator for the wealth paradox, where poorer households lack employment opportunities to send their children to work (Bhalotra and Heady, 2003).

Turning to the extensions of the main results, the hypothesis that mitigation channels reduce the use of child labor in households that were hit by a shock can only be robustly confirmed for the channel of social networks. Even though some evidence for financial access and income diversification as mitigation channels exists, data problems allow no final conclusion. The literature, however, suggest that these channels indeed play a role in mitigating the effect of shocks (see e.g. Dehejia and Gatti (2002) and Banerjee and Duflo (2007)). Moreover, the analysis of the lagged effect of shocks on children's time use leads to results that contradict the hypothesis posed in section 2.2 as well as the findings in the literature. Where I find the effect of shocks on child labor to be transitory, research related to the adult earnings prospects of former child laborers suggest the opposite (Posso, 2017). Have however in mind that this literature does not necessary divide between children that generally work and children that increase their work only as a response to a shock. Additionally, my results might understate any long-term negative effects of child labor on children, as I do not analyse if children's education is affected by the uptake of work after a shock. Lastly, the hypothesis that different community and individual shocks affect children's time use differently could be confirmed. Flooding and erosion are found to be most relevant to the overall effect of community shocks, while the wellbeing of the mother (death or illness) and the birth of a new baby are found to be the significant drivers of the effect of individual shocks on children's time spent on work and chores respectively.

A few limitations of my study are worth mentioning. Firstly, as explained above, all three econometric methods used are not optimal. Where the OLS and FE models might be unable to establish causality, the DiD analysis suffers from data limitations.

Nevertheless, all results point in the same direction, indicating the validity of the overall result that children increase their hours spent on work after being affected by a shock. Furthermore, the way information on the shock variable was acquired is not ideal for my analysis. The fact that the recorded shocks could have happened months before the interview and assuming that the effect of shocks on child labor tend to diminish over time suggests that the results reported here are underestimated. Any direct effects are likely bigger and further research should be conducted to confirm this.

Important policy recommendations can be derived from all of the above. Assuming altruistic parents who prefer not to send their children to work, the finding that households increase child labor as a response to shock signifies that other strategies to deal with shocks ex-ante or ex-post are not sufficiently available. The use of child labor as a mitigation strategy in times of shock suggests that banning child labor does not necessarily eradicate child labor. Much rather, households have to be equipped to deal with shocks in different ways as to not resort to child labor. The literature suggests that this could for example be done by providing formal credit or insurance (Morduch, 1995). Since especially poor people are vulnerable towards risk, providing these formal mitigation strategies is also a question of equality (Pradhan and Mukherjee, 2018). The insight that children's hours spent working increase directly after the shock but not permanently is an encouraging result. The literature on earning prospects suggests however that policy makers should ensure that increasing work to deal with shock does not negatively affect children's education (Emerson and Souza, 2011). Lastly, the differentiation of different shocks showed that children are especially affected by the death and illness of their mother and by flood and erosion. This has two implications. Firstly, women's health should be of major concern to policy makers. As mentioned above, maternal mortality is high in Ethiopia, but other factors like violence against women should also be considered. Secondly, policy makers should improve the response after environmental disasters such as floods and erosion. This might be especially relevant in rural areas.

7

Conclusion

High child labor rates in Ethiopia and the consensus in the literature that child labor is caused by negative income shocks raises the question of how children's time use is affected by experiencing community or individual shocks. To answer the question, a panel of children aged 5 to 15 from Ethiopia was analysed. Besides an OLS model, FE and DiD models were used to address endogeneity problems on the one hand and to overcome data problems on the other hand. This thesis contributes to the existing literature by incorporating the time spent on chores in the analysis to address that the time burden of children, and in particular of girls, could be understated if not for this adjustment. In addition, I identify child and household characteristics that increase any negative effect of shocks on children's time use and distinguish the different types of shocks that could be faced by a household. These differentiations are not commonly made or even missed completely in the literature. The assessment of mitigation channels and long term impacts completes the analysis.

This thesis provides evidence that children increase their hours spent on work when they experience a community or individual shock. With an increase of 0.16 hours per day on average, children increase their hours spent on work by more when they experience a community shock than when they experience an individual shock, where they increase their working hours by 0.12 hours per day on average. Compared to other determinants of child labor and the underlying sample average of children's working hours, the magnitude of this effect is considerable. The hours spent on chores are not significantly affected after either a community shock or individual shock. Certain child and household characteristics exacerbate the negative effect of shocks on children's time use. Rural children and poorer children increase their hours spent on chores significantly more than other children that are hit by a community shock or individual shock. Work is only heterogeneously affected by the age of children. Under any shock, 12-year-olds increase their working hours the most, while 5-year-olds increase their hours spent on chores the most. Possible explanations for these patterns include the availability of work as well as the already higher number of work and chore hours provided by older children. Lastly, no gendered effect is found.

The extensions of this analysis provide some important findings. The analysis of mitigation channels provides evidence that social networks lower the increase in hours spent working and significantly lower the increase in hours spent on chores when households are hit by a shock. Partly due to data issues, no final conclusion can be drawn concerning the other two channels, even though the results related to financial access point to it being a functioning mitigation channel. Looking at the effect of shocks that happened in a previous period, no negative long-term impact of shocks on children's time use can be determined. Lastly, distinguishing between the different shocks shows that especially flooding and erosion have an impact on children's work hours, while only erosion affects children's hours spent on chores. For individual shocks, only the arrival of a new baby significantly affects children's hours spent on chores, while the death and illness of the mother significantly affect children's work hours.

The evidence provided here emphasizes the importance of policy makers to address the lack of coping strategies that make households resort to child labor after a shock. In addition, it highlights that better knowledge about the nature of shocks and household reactions is needed to provide formal mitigation strategies tailored to the situations at hand. Ultimately, it reveals that child labor might be more complex to tackle than by simply making child labor illegal.

Bibliography

Abadie, A., Athey, S., Imbens, G., and Wooldridge, J. (2017). When should you adjust standard errors for clustering? *NBER Working Paper No. 24003*.

Bandara, A., Dehejia, R., and Lavie-Rous, S. (2015). The Impact of Income and Non-Income Shocks on Child Labor: Evidence from a Panel Survey of Tanzania. *World Development*, 67: pp. 218–237.

Banerjee, A. and Duflo, E. (2007). The Economic Lives of the Poor. *Journal of Economic Perspectives*, 21(1): pp. 141–167.

Basu, K., Das, S., and Dutta, B. (2010). Child labor and household wealth: Theory and empirical evidence of an inverted-U. *Journal of Development Economics*, 91(1): pp. 8–14.

Basu, K. and Van, P. (1998). The economics of child labor. *American Economic Review*, 88(3): pp. 412–427.

Becker, G. (1965). A Theory of the Allocation of Time. *The Economic Journal*, 75(299): pp. 493–517.

Beegle, K., Dehejia, R., and Gatti, R. (2006). Child labor and agricultural shocks. *Journal of Development Economics*, 81(1): pp. 81–96.

Beegle, K., Dehejia, R., and Gatti, R. (2009). Why Should We Care about Child Labor? The Education, Labor Market, and Health Consequences of Child Labor. *Journal of Human Resources*, 44(4): pp. 871–889.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How Much Should We Trust Differences-In-Differences Estimates? *The Quarterly Journal of Economics*, 119(1): pp. 249–275.

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

Boyden, J. (2022a). *Young Lives: an International Study of Childhood Poverty: Round 2 (2006).* 4th Edition. UK Data Service. SN: 6852. Data Collection. Available online: http://doi.org/10.5255/UKDA-SN-6852-4 [Accessed 01. May 2023].

Boyden, J. (2022b). *Young Lives: an International Study of Childhood Poverty: Round 3 (2009).* 4th Edition. UK Data Service. SN: 6853. Data Collection. Available online: http://doi.org/10.5255/UKDA-SN-6853-4 [Accessed 01. May 2023].

Boyden, J. (2022c). *Young Lives: an International Study of Childhood Poverty: Rounds 1-5 Constructed Files, 2002-2016.* 5th Edition. UK Data Service. SN: 7483. Data Collection. Available online: http://doi.org/10.5255/UKDA-SN-7483-5 [Accessed 01. May 2023].

Briones, K. (2017). *How Many Rooms Are There in Your House? Constructing the Young Lives Wealth Index. Technical Note 43.* Oxford: Young Lives. Available online: https://www.younglives.org.uk [Accessed 01. May 2023].

Briones, K. (2018). *A Guide to Young Lives Rounds 1 to 5 Constructed Files. Technical Note 48.* Oxford: Young Lives. Available online: https://www.younglives.org.uk [Accessed 01. May 2023].

Bryson, A., Dorsett, R., and Purdon, S. (2002). The Use of Propensity Score Matching in the Evaluation of Labour Market Policies. Working Paper 4, London: Department for Work and Pensions. Available online: https://www.researchgate.net/publication/30524857 [Accessed 26. May 2023].

Buvinic, M. and Gupta, G. (1997). Female-headed households and female-maintained families: Are they worth targeting to reduce poverty in developing countries? *Economic Development and Cultural Change*, 45(2): pp. 259–280.

Caliendo, M. and Kopeinig, S. (2008). Some Practical Guidance for the Implementation of Propensity Score Marching. *Journal of Economic Surveys*, 22(1): pp. 31–72.

Cameron, A. and Miller, D. (2015). A Practitioner's Guide to Cluster-Robust Inference. *Journal of Human Resources*, 50(2): pp. 317–372.

Cameron, L. and Worswick, C. (2003). The Labor Market as a Smoothing Device: Labor Supply Responses to Crop Loss. *Review of Development Economics*, 7(2): pp. 327–341.

Case, A., Paxson, C., and Ableidinger, J. (2004). Orphans in Africa: Parental Death, Poverty, and School Enrollment. *Demography*, 41(3): pp. 483–508.

Cherinet, A., Tadesse, C., and Abebe, T. (2022). Drought and Flood Extreme Events and Management Strategies in Ethiopia. *Journal of Geography and Natural Disaster*, 12(3): pp. 2–8.

Chiappori, P. (1988). Rational household labor supply. *Econometrica*, 56(1): pp. 63–90.

Chiappori, P. (1992). Collective Labor Supply and Welfare. *Journal of Political Economy*, 100(3): pp. 437–467.

Cockburn, J. and Dostie, B. (2007). Child Work and Schooling: The Role of Household Asset Profiles and Poverty in Rural Ethiopia. *Journal of African Economies*, 16(4): pp. 519–563.

Conway, D. and Schipper, L. (2011). Adaptation to climate change in Africa: Challenges and opportunities identified from Ethiopia. *Global Environmental Change*, 21: pp. 227–237.

CSA, C4ED, and UNICEF Ethiopia (2020). *Child Labour Analysis in Ethiopia 2020*. Addis Ababa: Central Statistical Agency of Ethiopia. Available online: https://www.unicef.org/ethiopia/media/3776/file/Report20.pdf [Accessed 26. May 2023].

Dammert, A., De Hoop, J., Mvukiyehe, E., and Rosati, F. (2018). Effects of public policy on child labor: current knowledge, gaps, and implications for program design. *World Development*, 110: pp. 104–123.

Dehejia, R. and Gatti, R. (2002). Child Labor: The Role of Income Variability and Access to Credit in a Cross-Section of Countries. *World Bank Policy Research Working Paper No. 2767*.

Demirgüç-Kunt, A., Klapper, L., Singer, D., and Ansar, S. (2022). *The Global Findex Database 2021: Financial Inclusion, Digital Payments, and Resilience in the Age of COVID-19.* . Washington, DC: World Bank. Available online: https://www.worldbank.org/en/publication/globalfindex/Datasec1 [Accessed 16. May 2023].

Dercon, S. (2002). Income Risk, Coping Strategies, and Safety Nets. *The World Bank Research Observer*, 17(2): pp. 141–166.

Dercon, S. (2005). Risk, Poverty and Vulnerability in Africa. *Journal of African Economies*, 14(4): pp. 483–488.

Dercon, S., De Weerdt, J., Bold, T., and Pankhurst, A. (2006). Group-based funeral insurance in Ethiopia and Tanzania. *World Development*, 34(4): pp. 685–703.

Duc, L., Penny, M., Boyden, J., Woldehanna, T., Galab, S., and Sanchez, A. (2022a). *Young Lives: an International Study of Childhood Poverty: Round 4 (2013-2014)*. 3rd Edition. UK Data Service. SN: 7931. Data Collection. Available online: http://doi.org/10.5255/UKDA-SN-7931-3 [Accessed 01. May 2023].

Duc, L., Penny, M., Boyden, J., Woldehanna, T., Galab, S., and Sanchez, A. (2022b). Young Lives: an International Study of Childhood Poverty: Round 5 (2016). 2nd Edition. UK Data Service. SN: 8357. Data Collection. Available online: http://doi.org/10.5255/UKDA-SN-8357-2 [Accessed 01. May 2023].

Duflo, E. (2003). Grandmothers and granddaughters: Old-age pensions and intrahousehold allocation in South Africa. *The World Bank Economic Review*, 17(1): pp. 1–25.

Duryea, S., Lam, D., and Levison, D. (2007). Effects of economic shocks on children's employment and schooling in brazil. *Journal of Development Economics*, 84(1): pp. 188–214.

Edmonds, E. and Pavcnik, N. (2005). Child Labor in the Global Economy. *The Journal of Economic Perspectives*, 19(1): pp. 199–220.

Edmonds, E. V. (2007). Chapter 57 Child Labor. in T. Paul Schultz and John A. Strauss (eds.). *Handbook of Development Economics*. Volume 4. Amsterdam: Elsevier: pp. 3607-3709.

Emerson, P. and Souza, A. (2003). Is There a Child Labor Trap? Intergenerational Persistence of Child Labor in Brazil. *Economic Development and Cultural Change*, 51(2): pp. 375–98.

Emerson, P. and Souza, A. (2011). Is Child Labor Harmful? The Impact of Working Earlier in Life on Adult Earnings. *Economic development and cultural change*, 59(2): pp. 345–385.

Ethiopian Central Statistic Agency and ICF (2016). Ethiopia Demographic and Health Survey 2016. Available online: https://dhsprogram.com/pubs/pdf/FR328/FR328.pdf [Accessed 26. May 2023].

Frempong, R. (2020). Do subsidies on seed and fertilizer lead to child labour? Evidence from Malawi. *Development Policy Review*, 41(2): pp. 1–23.

Gunnarsson, V., Orazem, P., and Sanchez, M. (2006). Child Labor and School Achievement in Latin America. *The World Bank Economic Review*, 20(1): pp. 31–54.

Hamilton, W. (1964). The genetical evolution of social behaviour. *Journal of Theoretical Biology*, 7(1): pp. 1–16.

Heckman, J., Ichimura, H., and Todd, P. (1997). Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *Review of Economic Studies*, 64(4): pp. 605–654.

Ibrahim, A., Abdalla, S., Jafer, M., Abdelgadir, J., and de Vries, N. (2018). Child labor and health: a systematic literature review of the impacts of child labor on child's health in low- and middle-income countries. *Journal of Public Health*, 41(1): pp. 18–26.

ILO (2016). *Global estimates of child labour: Results and trends, 2012-2016*. Geneva: International Labor Organisation. Available online: https://www.ilo.org/global/publications/books/WCMS575499/lang−−en/index .htm [Accessed 26. May 2023].

ILO and UNICEF (2021). *Child Labour: Global estimates 2020, trends and the road forward*. New York: International Labor Organisation and UNICEF. Available online: https://www.ilo.org/ipec/Informationresources/WCMS797515/lang−−en/index .htm [Accessed 26. May 2023].

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

Jann, B. (2017). KMATCH: Stata module module for multivariate-distance and propensity-score matching, including entropy balancing, inverse probability weighting, (coarsened) exact matching, and regression adjustment. Statistical Software Components S458346, Boston College Department of Economics. Available online: https://ideas.repec.org/c/boc/bocode/s458346.html [Accessed 26. May 2023].

Kibret, G., Ferede, A., Leshargie, C., Wagnew, F., Ketema, D., and Alebel, A. (2019). Trends and spatial distributions of HIV prevalence in Ethiopia. *Infectious Diseases of Poverty*, 8(1): pp. 1–9.

King, G. and Nielsen, R. (2019). Why Propensity Scores Should Not Be Used for Matching. *Political Analysis*, 27(4): pp. 1–20.

Kochar, A. (1999). Smoothing Consumption by Smoothing Income: Hours-of-Work Responses to Idiosyncratic Agricultural Shocks in Rural India. *The Review of Economics and Statistics*, 81(1): pp. 50–61.

Lechner, M., Rodriguez-Planas, N., and Fernández Kranz, D. (2015). Difference-in-Difference Estimation by FE and OLS when there is Panel Non-Response. *IZA Discussion Paper No. 9490*.

Lee, J., Kim, H., and Rhee, D. (2021). No harmless child labor: The effect of child labor on academic achievement in francophone Western and Central Africa. *International Journal of Educational Development*, 80: pp. 1–11.

Manser, M. and Brown, M. (1980). Marriage and Household Decision-Making: A Bargaining Analysis. *International Economic Review*, 21(1): pp. 31–44.

Marini, M. M. and Shelton, B. A. (1993). Measuring Household Work: Recent Experience in the United States. *Social Science Research*, 22(4): pp. 361–382.

Mitra, D. (2020). Is There a Culture of Child Labour? The Decision-Making Process of Working Among Girl Beedi Rollers in Jhalda Region of Purulia, West Bengal. in A. Posso (Ed.). *Child Labor in the Developing World: Theory, Practice and Policy*. Singapore: Springer Nature Singapore Pte Ltd.: pp. 83-109.

Moges, D. and Bhat, H. (2021). Climate change and its implications for rainfed agriculture in Ethiopia. *Journal of Water and Climate Change*, 12(4): pp. 1229–1244.

Morduch, J. (1995). Income Smoothing and Consumption Smoothing. *Journal of Economic Perspectives*, 9(3): pp. 103–111.

Moulton, B. (1986). Random group effects and the precision of regression estimates. *Journal of Econometrics*, 32(3): pp. 385–397.

OCHA (2011). Eastern Africa Drought - Humanitarian Report No. 3. Available online: https://reliefweb.int/report/burundi/eastern-africa-drought-humanitarian-report-no-3 [Accessed 17. May 2023]. New York: United Nations Office for the Coordination of Humanitarian Affairs.

Outes-Leon, I. and Sanchez, A. (2008). *An Assessment of the Young Lives Sampling Approach in Ethiopia. Technical Note 1.* Oxford: Young Lives. Available online: https://www.younglives.org.uk [Accessed 01. May 2023].

Pieper, T. (2022). The Effect of Orphanhood on Schooling: Insights from rural Ethiopia. Master Thesis. Graduate School of Economics and Political Science, Universidad Carlos III de Madrid. Available online: https://lusem.lu.se/media/ekh/medeg-papers/Madrid-2022-Theresa.pdf.

Posso, A. (2017). Child Labour's effect on long-run earnings: An analysis of cohorts. *Economic Modelling*, 64: pp. 465–472.

Posso, A. (2020). Introduction. in A. Posso (Ed.). *Child Labor in the Developing World: Theory, Practice and Policy.* Singapore: Springer Nature Singapore Pte Ltd.: pp. 1-13.

Pradhan, K. and Mukherjee, S. (2018). Covariate and Idiosyncratic Shocks and Coping Strategies for Poor and Non-poor Rural Households in India. *Journal of Quantitative Economics*, 16: pp. 101–127.

Ranjan, P. (1999). An economic analysis of child labor. *Economics Letters*, 64: pp. 99–105.

Rosenbaum, P. and Rubin, D. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1): pp. 41–55.

Stinson, L. L. (1999). Measuring how people spend their time: a time-use survey design. *Monthly Labor Review*, 122(8): pp. 12–19.

UN News (2009). Ethiopia faces large food shortfall for over 6 million drought victims. Available online: https://news.un.org/en/story/2009/10/318562 [Accessed 17. May 2023].

UNCERF (2006). Ethiopia 2006 Drought - Executive Summary. Available online: https://cerf.un.org/sites/default/files/resources/Ethiopia2006240807Final.pdf [Accessed 17. May 2023]. New York: UN Central Emergency Response Fund.

UNICEF (2019). *Maternal Mortality.* Data Collection. Available online: https://data.unicef.org/topic/maternal-health/maternal-mortality/ [Accessed 16. May 2023].

Wooldridge, J. M. (2012). *Introductory Econometrics- A modern approach.* Mason: South-Western Cengage Learning.

Yamano, T. and Jayne, T. (2005). Working-Age Adult Mortality and Primary School Attendance in Rural Kenya. *Economic Development and Cultural Change*, 53(3): pp. 619–53.

Young Lives (2014). *Ethiopia Community Data Dictionary Round 4.* Oxford: Young Lives. Available online: https://doc.ukdataservice.ac.uk/doc/7931/mrdoc/pdf/7931r4ethiopiadatadictionaries.pdf [Accessed 02. May 2023].

Young Lives (2018). *Young Lives Survey Design and Sampling (Round 5) Ethiopia*. Oxford: Young Lives. Available online: https://assets.publishing.service.gov.uk/media/5b9a93c4ed915d665412ca27/ETHIOPIA-SurveyDesign-Factsheet-Jan180.pdf [Accessed 02. May 2023].

Appendix A

Appendix

Table A.1: Original vs. Restricted Sample: Community Shock

	Original Sample		Restricted Sample	
	Hours work	Hours chores	Hours work	Hours chores
Community Shock	1.339***	0.336*	1.216***	0.129
	(0.194)	(0.179)	(0.210)	(0.168)
Constant	1.385***	2.611***	1.365***	2.698***
	(0.179)	(0.149)	(0.179)	(0.150)
Round Controls	Yes	Yes	Yes	Yes
N	8831	8831	7220	7220
R^2	0.101	0.043	0.073	0.023

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Round controls: dummies for study round 2-4 (baseline category round 5). OLS estimation. Robust standard errors clustered at the community level in parentheses.
Source: Own calculations based on Young Lives rounds 2-5 and Rounds 1-5 Constructed Files.

Table A.2: Original vs. Restricted Sample: Individual Shock

	Original Sample		Restricted Sample	
	Hours work	Hours chores	Hours work	Hours chores
Individual Shock	0.0703	0.198***	0.0661	0.214***
	(0.0513)	(0.0444)	(0.0592)	(0.0496)
Constant	1.821***	2.677***	1.763***	2.691***
	(0.0615)	(0.0433)	(0.0608)	(0.0435)
Round Controls	Yes	Yes	Yes	Yes
N	8835	8835	7220	7220
R^2	0.018	0.039	0.009	0.025

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Round controls: dummies for study round 2-4 (baseline category round 5). OLS estimation. Robust standard errors clustered at the child level in parentheses.
Source: Own calculations based on Young Lives rounds 2-5 and Rounds 1-5 Constructed Files.

Table A.3: Clustered vs. robust standard errors: Baseline OLS model

	Hours work				Hours chores			
	Clustered s.e.	Robust s.e.	Clustered s.e.	Robust s.e.	Clustered s.e.	Robust s.e.	Clustered s.e.	Robust s.e.
Community Shock	0.425***	0.425***			-0.156*	-0.156***		
	(0.0978)	(0.0559)			(0.0899)	(0.0477)		
Individual Shock			0.123**	0.123***			0.179***	0.179***
			(0.0488)	(0.0475)			(0.0429)	(0.0426)
Age 8	0.999***	0.999***	0.835***	0.835***	-0.0988	-0.0988	-0.145	-0.145
	(0.339)	(0.157)	(0.165)	(0.156)	(0.592)	(0.149)	(0.155)	(0.147)
Age 12	1.290***	1.290***	1.288***	1.288***	1.463***	1.463***	1.469***	1.469***
	(0.140)	(0.0947)	(0.0950)	(0.0948)	(0.178)	(0.0921)	(0.0914)	(0.0915)
Age 15	1.186***	1.186***	1.031***	1.031***	0.633	0.633***	0.594***	0.594***
	(0.309)	(0.169)	(0.184)	(0.168)	(0.559)	(0.155)	(0.165)	(0.153)
Male	1.544***	1.544***	1.538***	1.538***	-1.486***	-1.486***	-1.481***	-1.481***
	(0.177)	(0.0455)	(0.0524)	(0.0457)	(0.0952)	(0.0400)	(0.0454)	(0.0400)
Wealth Index	-1.524***	-1.524***	-1.641***	-1.641***	-0.416	-0.416***	-0.377**	-0.377**
	(0.304)	(0.184)	(0.201)	(0.184)	(0.337)	(0.158)	(0.170)	(0.157)
Rural	0.585***	0.585***	0.673***	0.673***	0.606**	0.606***	0.592***	0.592***
	(0.182)	(0.0743)	(0.0822)	(0.0739)	(0.295)	(0.0659)	(0.0729)	(0.0651)
Constant	0.637	0.637	1.195*	1.195*	4.227***	4.227***	3.536***	3.536***
	(0.864)	(0.669)	(0.639)	(0.626)	(1.168)	(0.428)	(0.433)	(0.416)
Personal and Household Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7220	7220	7220	7220	7220	7220	7220	7220
R^2	0.295	0.295	0.290	0.290	0.256	0.256	0.255	0.255

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table depicts the results of the baseline OLS model including the full set of controls using clustered standard errors (clustered at the community level for the analysis of community shocks and at the child level for the analysis of individual shocks) and heteroskedasticity robust standard errors. For a description of the full set of controls see tables 5.1 and 5.2.

Source: Own calculations based on Young Lives rounds 2-5 and Rounds 1-5 Constructed Files.

Figure A.1: Hausman Test: Individual and Community shock and hours work

	Coefficients (b) fixed	(B) .	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
shock_comm	.1588674	.3562941	-.1974267	.0389859
round3	.0638017	-.1237587	.1875605	.0898812
age8	1.239467	1.449787	-.2103195	.0915573
age12	1.497759	1.486267	.0114919	.0540258
age15	1.531586	1.670669	-.139083	.0495268
oldest	-.0500959	-.0631928	.0130969	.1031295
rel_HHhead	.133537	.115791	.0177461	.0398317
wealth_index	-.193692	-1.269536	1.075844	.2809346
land_owned	.0002464	.0004439	-.0001975	.0001319
own_livest~k	.1844752	.6013902	-.416915	.0858329
school_sup~y	-1.46193	-1.642825	.1808952	.2166077
edu_caregi~r	.0031702	.0044533	-.0012831	.0051706
HHsize	-.0207476	.0180054	-.038753	.0183284
gender_car~r	.2611537	.0997014	.1614523	.0644525
rural	.4882697	.6510598	-.1627901	.2226148
region	-.0846611	-.0735473	-.0111139	.0457714

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

Test: Ho: difference in coefficients not systematic

chi2(16) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 99.01
Prob>chi2 = 0.0000

	Coefficients (b) fixed	(B) .	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
shock_ind	.1149765	.1043525	.010624	.0363086
round3	-.0076169	-.0859842	.0783673	.0862304
age8	1.303436	1.427123	-.123687	.0885706
age12	1.42053	1.435192	-.0146622	.0488751
age15	1.526947	1.649912	-.1229658	.050014
oldest	-.0554049	-.0659308	.0105259	.1027066
rel_HHhead	.1293445	.1163953	.0129492	.0396466
wealth_index	-.2105668	-1.38426	1.173693	.2804685
land_owned	.0002577	.0005112	-.0002534	.0001307
own_livest~k	.2021229	.6318343	-.4297114	.0852899
school_sup~y	-1.469826	-1.657932	.1881064	.2152126
edu_caregi~r	.0014001	.0041879	-.0027878	.0050884
HHsize	-.0178117	.0249665	-.0427782	.0182638
rural	.4926603	.7286808	-.2360204	.2225909
region	-.0886922	-.0840886	-.0046036	.0457186

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

Test: Ho: difference in coefficients not systematic

chi2(15) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 76.96
Prob>chi2 = 0.0000

Note: The null hypothesis states that the unique errors are not correlated with the regressors and that a random effects model should be preferred. With the $Prob > chi2$ statistic equal to zero, this hypothesis can be rejected.
Source: Own calculations based on Young Lives rounds 2-5 and Rounds 1-5 Constructed Files.

Figure A.2: Hausman Test: Individual and Community shock and hours chores

	Coefficients (b) fixed	(B) .	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
shock_comm	-.0657752	-.1212942	.055519	.0348976
round3	.3963753	.482362	-.0859867	.0795842
age8	.9779085	.8074622	.1704463	.0812184
age12	1.22491	1.285589	-.0606796	.0479458
age15	1.51382	1.51396	-.0001396	.0440007
oldest	.2022138	.1972077	.0050061	.0910944
rel_HHhead	-.0565198	-.0337331	-.0227867	.0352504
wealth_index	-.0683068	-.5191245	.4508177	.2486937
land_owned	-.0005348	-.0004607	-.0000741	.0001198
own_livest~k	-.1792278	-.1524016	-.0268262	.0762292
school_sup~y	-.1871018	-.4660696	.2789677	.1938495
edu_caregi~r	.0027577	-.0012186	.0039762	.0045651
HHsize	-.0238265	.0264156	-.050242	.0162493
gender_car~r	-.0594893	-.2305031	.1710138	.0575806
rural	.0886963	.5955938	-.5068975	.1956987
region	-.0733036	-.0133506	-.059953	.0401304

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

Test: Ho: difference in coefficients not systematic

chi2(16) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 124.83
Prob>chi2 = 0.0000

	Coefficients (b) fixed	(B) .	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
shock_ind	.0455914	.1679259	-.1223345	.0326049
round3	.4027217	.4182273	-.0155056	.0766212
age8	.9700798	.8645032	.1055766	.0788687
age12	1.263209	1.362981	-.0997717	.0435208
age15	1.541981	1.586937	-.0449557	.044575
oldest	.2031814	.1941182	.0090632	.090902
rel_HHhead	-.0534307	-.0321057	-.021325	.0351711
wealth_index	-.071265	-.4460448	.3747797	.24887
land_owned	-.0005402	-.0005058	-.0000344	.0001196
own_livest~k	-.1859467	-.1703345	-.0156123	.0759946
school_sup~y	-.194692	-.4887205	.2940285	.1935133
edu_caregi~r	.0028905	-.00085	.0037405	.0045017
HHsize	-.0248651	.0212284	-.0460934	.0162359
rural	.0871926	.5832955	-.4961029	.1958382
region	-.0729719	-.0104446	-.0625273	.0400961

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

Test: Ho: difference in coefficients not systematic

chi2(15) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 108.00
Prob>chi2 = 0.0000

Note: The null hypothesis states that the unique errors are not correlated with the regressors and that a random effects model should be preferred. With the $Prob > chi2$ statistic equal to zero, this hypothesis can be rejected.
Source: Own calculations based on Young Lives rounds 2-5 and Rounds 1-5 Constructed Files.

Table A.4: Pre-treatment trends: Non-matched sample

Change in	Treated	Non-Treated	Difference	N
		Community Shock		
Hours work	0.879	0.259	0.619***	1022
Hours chores	2.000	1.289	0.711***	1022
		Individual Shock		
Hours work	0.722	0.964	-0.242	692
Hours chores	1.515	1.402	0.114	692

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Changes in outcomes between survey rounds 2 and 3 for treated and untreated children (those who do and do not experience a community or individual shock in round 4, while not experiencing a shock in rounds 2 and 3) are depicted.
Source: Own calculations based on Young Lives rounds 2-4 and Rounds 1-5 Constructed Files. The sample includes only those individuals that are present in all three rounds and that do not experience any type of shock in the two pre-treatment periods.

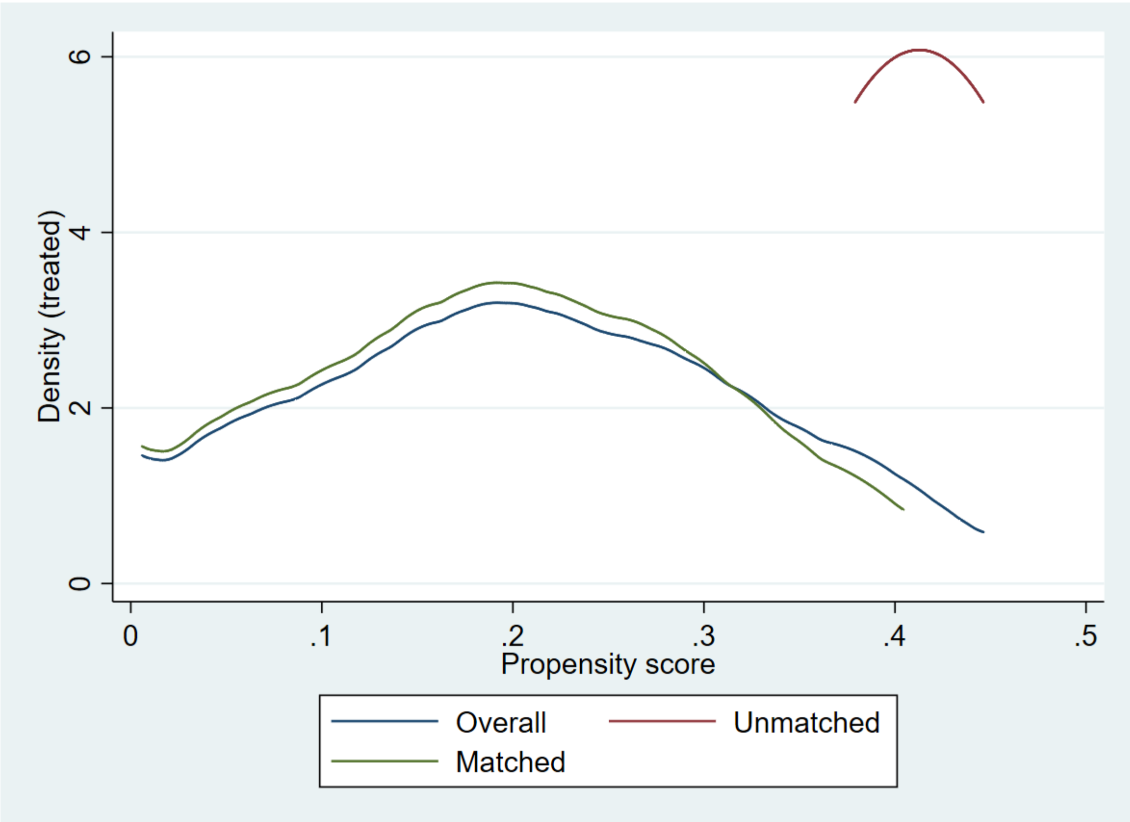
Table A.5: Pre-treatment trends: Matched sample

Change in	Treated	Non-Treated	Difference	N
		Community Shock		
Hours work	0.857	0.911	-0.054	462
Hours chores	1.929	1.532	0.397	462
		Individual Shock		
Hours work	0.800	1.071	-0.271	480
Hours chores	1.529	1.755	-0.226	480

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

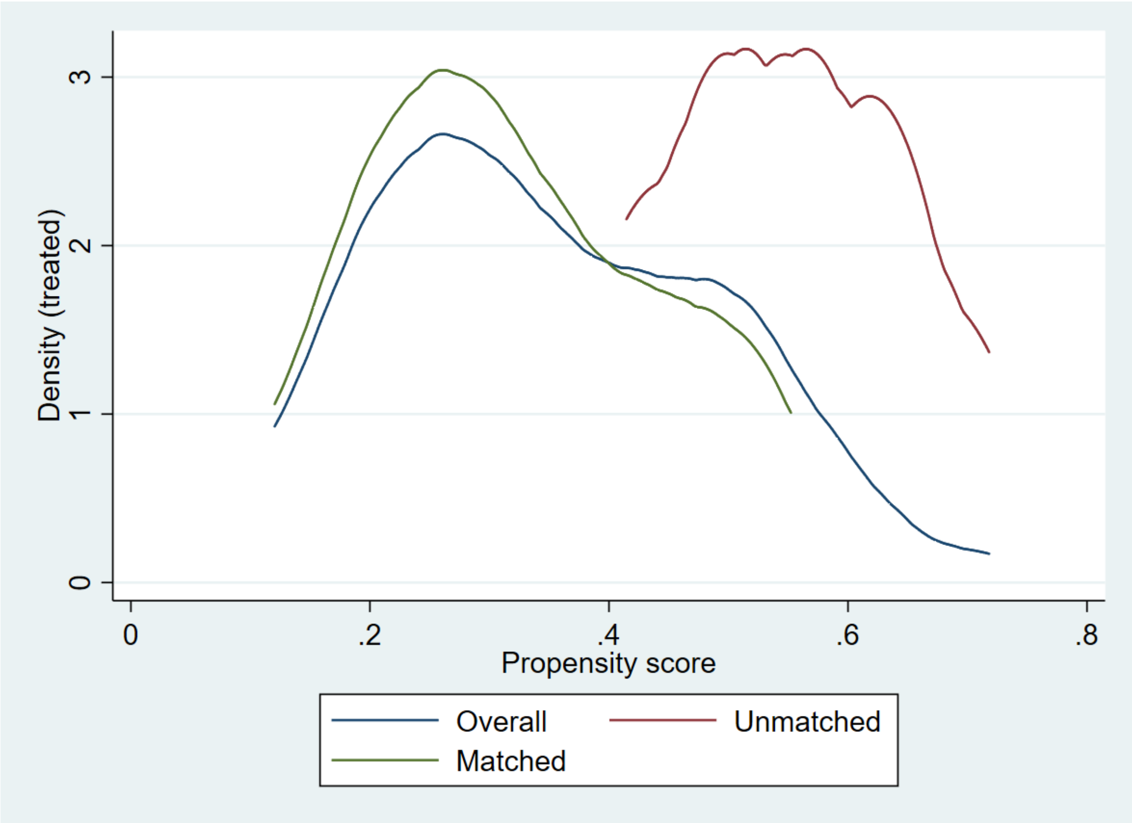
Note: Changes in outcomes between survey rounds 2 and 3 for treated and untreated children (those who do and do not experience a community or individual shock in round 4, while not experiencing a shock in rounds 2 and 3) are depicted. The matched sample is used.
Source: Own calculations based on Young Lives rounds 2-4 and Rounds 1-5 Constructed Files.

Figure A.3: Community Shock: Propensity score density of the matched, unmatched and overall sample



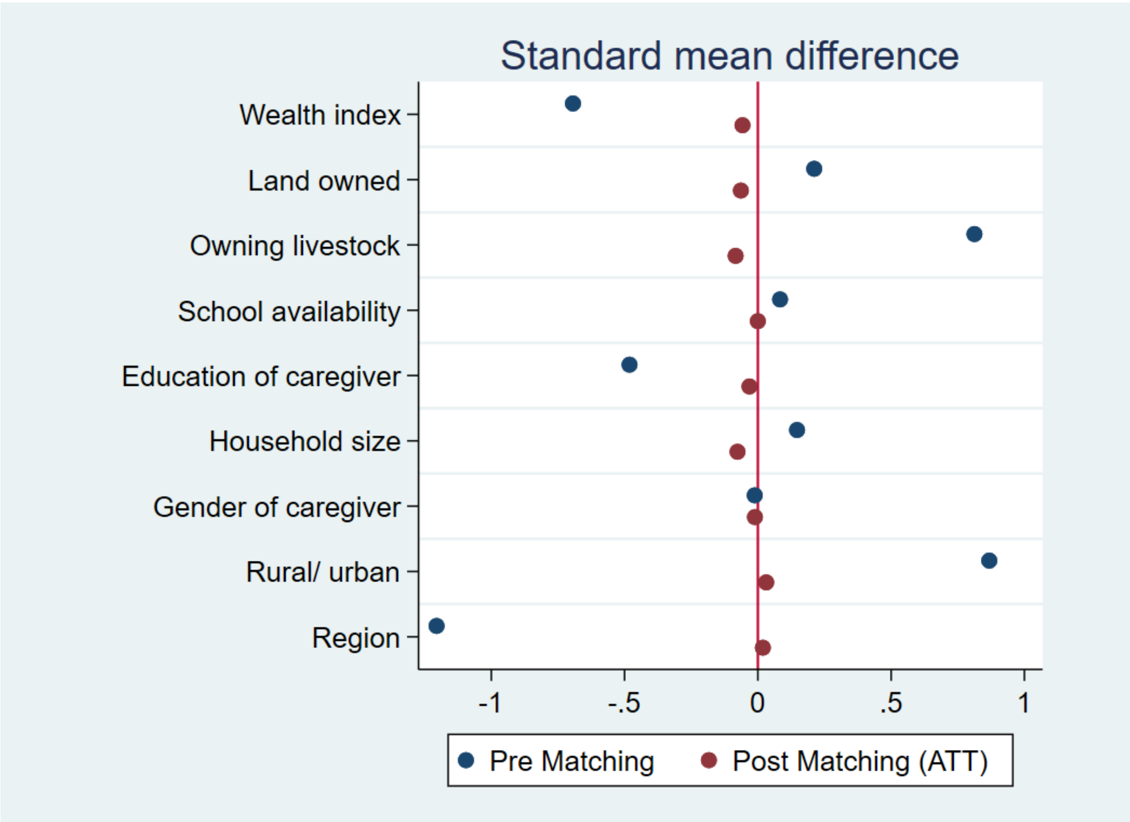
Note: Graph depicts the propensity score density of the matched, unmatched and overall sample. The sample consists of treated and untreated children that did not experience a shock in survey rounds 2 and 3.
Source: Own calculations based on Young Lives rounds 2-4 and Rounds 1-5 Constructed Files.

Figure A.4: Individual Shock: Propensity score density of the matched, unmatched and overall sample



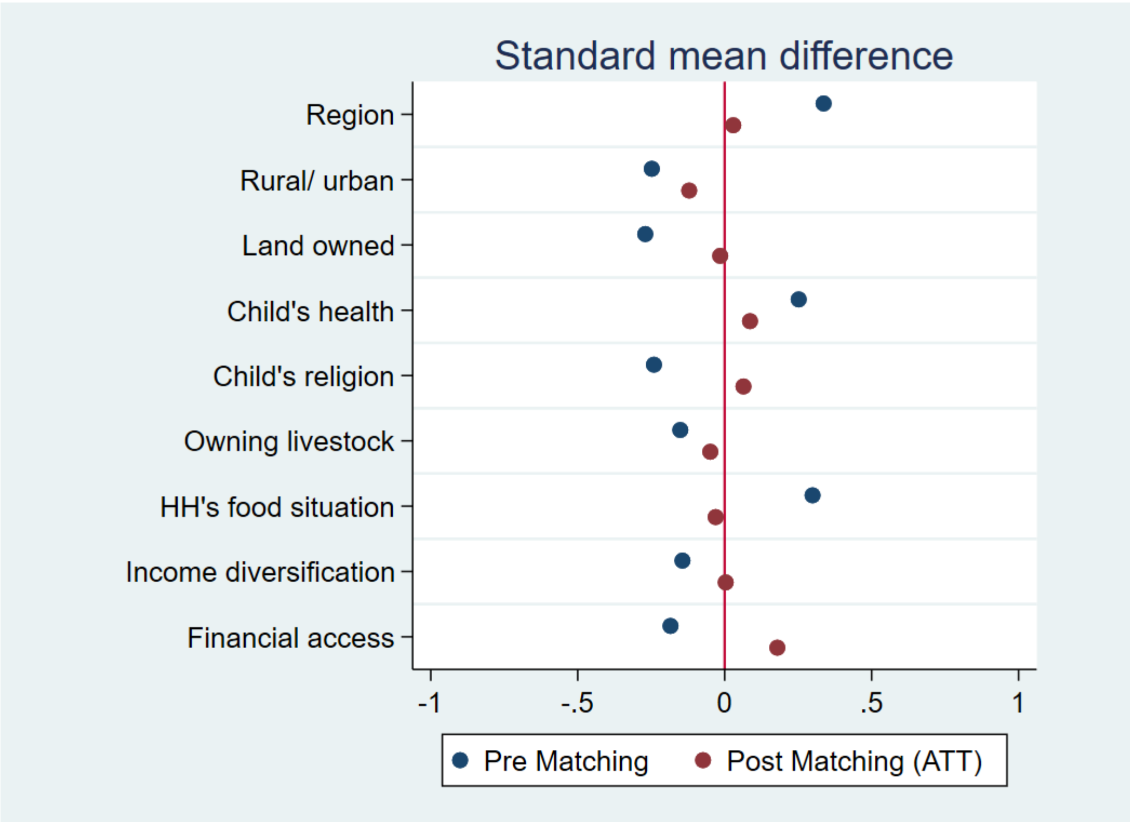
Note: Graph depicts the propensity score density of the matched, unmatched and overall sample. The sample consists of treated and untreated children that did not experience a shock in survey rounds 2 and 3.
Source: Own calculations based on Young Lives rounds 2-4 and Rounds 1-5 Constructed Files.

Figure A.5: Community Shock: Std. mean differences pre and post matching



Note: Graph depicts the standard mean differences of matching covariates pre and post matching. The sample consists of treated and untreated children that did not experience a shock in survey rounds 2 and 3.
Source: Own calculations based on Young Lives rounds 2-4 and Rounds 1-5 Constructed Files.

Figure A.6: Individual Shock: Std. mean differences pre and post matching



Note: Graph depicts the standard mean differences of matching covariates pre and post matching. The sample consists of treated and untreated children that did not experience a shock in survey rounds 2 and 3.
Source: Own calculations based on Young Lives rounds 2-4 and Rounds 1-5 Constructed Files.

Table A.6: Complete regression output FE model: Community and individual shocks on hours work

	Community Shock	Individual Shock
Shock	0.159*	0.115*
	(0.0876)	(0.0596)
Round 3	0.0638	-0.0076
	(0.183)	(0.124)
Age 8	1.239***	1.303***
	(0.200)	(0.148)
Age 12	1.498***	1.421***
	(0.247)	(0.0936)
Age 15	1.532***	1.527***
	(0.193)	(0.0988)
Oldest	-0.0501	-0.0554
	(0.150)	(0.134)
Relation to Household head	0.134**	0.129*
	(0.0520)	(0.0676)
Wealth Index	-0.194	-0.211
	(0.330)	(0.341)
Land owned	0.0002	0.0003
	(0.000)	(0.000)
Owning animals	0.184	0.202*
	(0.136)	(0.115)
School availability	-1.462***	-1.470***
	(0.412)	(0.470)
Education caregiver	0.0032	0.0014
	(0.00376)	(0.00542)
Household size	-0.0207	-0.0178
	(0.0181)	(0.0231)
Gender caregiver	0.261**	
	(0.116)	
Rural	0.488*	0.493**
	(0.195)	(0.244)
Region	-0.0847***	-0.0887**
	(0.0308)	(0.0352)
Constant	1.239*	1.817***
	(0.730)	(0.548)
N	7220	7220
R^2	0.093	0.091

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ **Note:** Controls are explained in tables 5.1 and 5.2. Standard errors clustered at the community and child level respectively. **Source:** Own calculations based on YL rounds 2-4 and Rounds 1-5 Constructed Files.

Table A.7: Effect of different community shock on Hours work and Hours chores

	Hours work	Hours chores
(I) Drought	0.0551	-0.0285
	(0.0652)	(0.0911)
(II) Flooding	0.152*	0.110
	(0.0868)	(0.0743)
(III) Erosion	0.203*	0.401*
	(0.104)	(0.230)
(IV) Frost	0.165	0.0273
	(0.110)	(0.0992)
(V) Pest	0.143	0.0221
	(0.0954)	(0.0641)
N	7220	7220

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table contains the coefficients and standard errors estimated for the shock variable of five different FE models. The community shock is defined as a drought (I), flooding (II), erosion (III), frost (IV) or pest on crops (including crop failure), storage or livestock (V).
All models include the following controls: dummies for age 8, 12 and 15 (baseline category: Age 5), for survey round 3 (baseline category round 4) and for being the oldest child in the HH and the child's relation to the HH head, the region, wealth index, the amount of land owned by the HH, dummies for owning any livestock, for rural/urban HH and for the availability of schools, the education and gender of the caregiver, and the HH size.
Robust standard errors clustered at community level in parentheses. The R^2 are as follows: (I): 0.148 (work), 0.052 (chores); (II): 0.149 (work), 0.055 (chores); (III) 0.150 (work), 0.056 (chores); (IV): 0.150 (work), 0.052 (chores); (V): 0.152 (work), 0.053 (chores)
Source: Own calculations based on Young Lives rounds 2-5 and Rounds 1-5 Constructed Files.

Table A.8: Effect of different individual shock on Hours work and Hours chores

	Hours work	Hours chores
(I) Theft/Destruction	0.159	0.117
	(0.101)	(0.0950)
(II) House	0.193	0.0059
	(0.210)	(0.215)
(III) Death: father	-0.110	0.0372
	(0.210)	(0.163)
(IV) Death: mother	0.485*	-0.235
	(0.265)	(0.213)
(V) Illness: father	0.0473	0.0311
	(0.0848)	(0.0831)
(VI) Illness: mother	0.251***	0.110
	(0.0773)	(0.0736)
(VII) Separation	-0.00372	0.266
	(0.244)	(0.187)
(VIII) New Birth	-0.0683	0.318***
	(0.0961)	(0.0927)
N	7220	7220

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table contains the coefficients and standard errors estimated for the shock variable of five different FE models. The individual shock is defined as theft or destruction of cash, crops, livestock or consumer goods (I), fire or collapse of housing (II), the death of the father (III), the death of the mother (IV), the illness of the father (V), the illness of the mother (VI), a separation (e.g. from the parents) (VII) or a new birth/ addition to the family (VIII). All models include the following controls: dummies for age 8, 12 and 15 (baseline category: Age 5), for survey round 3 Baseline category for age: age 5. Controls include: dummies for survey round 3 (baseline category round 4) and for being the oldest child in the HH and the child's relation to the HH head, the region, wealth index, the amount of land owned by the HH, dummies for owning any livestock, for rural/urban HH and for the availability of schools, the education of the caregiver, and the HH size. Robust standard errors clustered at child level in parentheses. The R^2 are as follows: (I): 0.152 (work), 0.052 (chores); (II): 0.150 (work), 0.052 (chores); (III) 0.150 (work), 0.051 (chores); (IV): 0.147 (work), 0.052 (chores); (V): 0.150 (work), 0.052 (chores); (VI): 0.150 (work), 0.054 (chores); (VII): 0.150 (work), 0.052 (chores); (VIII): 0.149 (work), 0.056 (chores)

Source: Own calculations based on Young Lives rounds 2-5 and Rounds 1-5 Constructed Files.