Topics in Economics of Development

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To my sunshine C.

Still I rise

Maya Angelou

Just like moons and like suns,
With the certainty of tides,
Just like hopes springing high,
Still I'll rise.

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0.1 Introduction

This thesis contains three standalone chapters that fall under the broad banner of development economics.

The first chapter contributes to the debate on the local impact of mineral resources in developing countries. Precisely, I analyse the effect of the boom in the world price of gold during the early 2000s on child labour and schooling outcomes in Mali. While empirical studies document the positive impacts of resource booms on real income (Hilson, 2009; Loayza and Rigolini, 2016), the effect on other measures of human well-being, such as education, is less clear. Given a boom in gold mining brings development to local communities in the form of jobs, increased household income and improved infrastructure (Land, 2015), one would expect to observe an increase in school enrolment and a decrease child labour rate (an income effect). This being said, the accessible and profitable nature of gold mining, especially in small-scale mining could constitute an employment source for young adults and children. This could lead families to disregard their children's education in pursuit of short-term income and push them to work, leading to a lower level of education (a substitution effect). This chapter is devoted to examine which of these effects dominate.

While large-scale mining (LSM) produces most of the gold in Mali, another form of mining known as artisanal and small-scale mining (ASM) coexists alongside. I construct a rich, repeated cross-sectional dataset by combining the geocoded mining location of every registered ASM and LSM site[1] with nationally representative household surveys and child labour surveys from the Demographic and Health Survey (DHS) collected in 2001 (before the gold price increase) and 2012 (after the gold price increase).

The chapter's main results suggest that the substitution effect of a boom

[1]This information was acquired from Infomine and the Direction Nationale de la Géologie et des Mines (DNGM) in Mali.

in the world price of gold dominates the income effect, with households pushing their kids out of school to supplement their incomes.

Many rural Ethiopian households rely heavily on agriculture as their primary source of income. Since most crop production in Ethiopia is rain-fed, rural household revenue is extremely vulnerable to precipitation shocks (Ademe et al., 2019). Moreover, given that both insurance markets and credit markets are weakly developed, and climate change is forecasted to increase the variability and intensity of these shocks[2], understanding the labour market responses of rural households to these shocks is of great importance to policy makers. This is the subject of Chapter 2.

Using data from a large and nationally representative sample of rural households, combined with monthly re-analysis precipitation data for the period 1981-2014, I examine how precipitation shocks impact household participation in labour activities.[3] Particular emphasis is given to how time-allocation responses vary across gender and how it changes according to the current month. I find that all individuals increase their time allocation to casual public work, largely consisting of participating in the government-run Public Works programme that provides food, cash, or a mixture of both, in return for work.

Additionally, I exploit the heterogeneous impact of precipitation on farming to examine the channels through which precipitation affect labour time allocation[4]. To do this, I take advantage of the large scale irrigation investment in dams that Ethiopia started in the 1960s as part of the government-owned state farms programme (Awulachew, 2019). While dams are clearly beneficial (they allow water to be stored for later use ultimately leading to less volatility in income), calculating the magnitude of benefit is important for policy makers. To this end, I split the sample into rain-fed areas and areas with irrigated

[2]See for instance: Hulme et al. (2001); Desanker and Magadza (2001); Hulme et al. (2005)

[3]These labour activities include household agricultural activities, non-agricultural work (self-employment or not), casual public work, (salaried) wage work, unpaid traineeships and household chores.

[4]The strategy implemented mirrors that of Sarsons (2011); Maitra and Tagat (2019a); Strobl and Strobl (2011); Blanc and Strobl (2014)

systems and test whether the time allocation responses to precipitation shocks differ by the areas in which households reside. I find almost no effects on the time allocation to labour activities in districts with irrigation. My results should help to inform policy makers on part of the true value of irrigation programs, thereby assisting in computing the shadow price of future large scale irrigation systems.

The chapter makes three main contributions to the existing literature. The first contribution lies in providing a deeper understanding of how gender differences in the allocation of time come about in rural Ethiopia, giving more insight into intra-household responses to weather shocks. Second, although several studies provide evidence on the effect of precipitation shocks on household labour time allocation, studies that examine variations in precipitation in each month during the growing season are still nascent. Considering monthly variations in precipitation shocks enables me to analyse if and how a specific month of the growing season is essential in contributing to household wellbeing.Third, I present evidence on the importance of major infrastructure projects, such as irrigation dams, in protecting against weather shocks.

Finally, Chapter 3 analyses the household determinants of child mistreatment in developing countries.[5] Child mistreatment is of particular concern for development, but what factors contribute to higher risks of physical and emotional ill-treatment? How can these findings be used by policymakers?

Notwithstanding numerous media reports on child mistreatment incidents, detailed analyses of the contributing risk and protective factors of child mistreatment from a nationally representative sample have been predominantly limited to developed countries.[6] This chapter sheds light on what household characteristics are associated with child mistreatment in developing countries,

[5] According to the World Health Organization (WHO), child mistreatment includes all forms of physical, sexual, emotional ill-treatment and neglect involving child labour and exploitation (WHO, 2016).

[6] See for example Markowitz and Grossman (1998, 2000), Paxson and Waldfogel (1999, 2002, 2003), Brooks-Gunn and Duncan (1997) and McLoyd (1998).

using the Ivory Coast as its point of study. To do this, I use the first nationally representative Ivorian household survey that includes a component of discipline methods applied by caregivers to their children. While the paper is descriptive, the correlative evidence on the household characteristics of child mistreatment should help decision-makers identify households at high risk of child mistreatment and enable them to tailor strategies targeted at prevention.

The structure of the thesis is as described in this introduction. Chapter 1 assesses the local impact of the boom in gold world price in the 2000s on child labour and schooling decisions in Mali, Chapter 2 addresses rural Ethiopian households' responses to precipitation shocks, and Chapter 3 examines the household characteristics associated with child abuse in Ivory Coast. Most of the Tables and Figures relevant to each Chapter are included in the main body of the Thesis, but additional Tables and Results are included in the Appendix, with a section for each Chapter.

Chapter 1

Gold boom, Child Labour and Schooling: Evidence from Mali

1.1 Introduction

Empirical evidence suggests that mineral resources can impact local communities both positively and negatively. In the presence of weak institutions, mineral resources could lead to violent conflicts and crime by increasing the rents from appropriating that resource (Axbard et al., 2019). Other negative spillovers through an effect on pollution, comprise the loss of agricultural productivity and hence reductions in the living standards of farmers in the vicinity of mines (Aragón and Rud, 2016). At the same time, an influential body of the literature discusses that mineral resources may be a blessing rather than a curse for developing countries. Positive impacts could arise from a fiscal channel in which the revenue windfall generated by the mineral resources enables governments to support higher public spending and improve the provision of public goods such as roads, electricity and schools (Aragón and Rud, 2013). Be that as it may, researchers argue that most of the positive impacts are found through a market channel. They explain that mineral resource booms can be thought of as local employment development boosts and thus increase local income (Aragón and Rud (2013); Land (2015); Kotsadam and Tolonen (2016); Loayza and Rigolini (2016); Thomas (2010)). Indeed, by employing local workers and purchasing local goods and services, a mining boom should raise nominal wages, increase non-mine employment opportunities and improve local welfare and thus reduce poverty (Land, 2017). While this predicts a possible positive impact of resource booms on real income, the effect on other measures of human well-being, such as education is less clear. If one thinks of mining as bringing development to local communities such as jobs, increased household income or better infrastructure, we could observe an increase in school enrolment and a decreased child labour rate (income effect). This being said, the accessible and profitable nature of artisanal and small-scale mining in the vicinity of large scale mines could constitute an employment source for young adults and children. This could in turn lead families to disregard their children's education and to incite them to work, leading to a lower level of education (substitution effect). This paper contributes to the debate by analysing the impact of the boom in international gold prices on child labour and schooling outcomes in Mali.

I argue that Mali is a compelling case, as over the past twenty years, the country has seen its potential in gold mining increase. Today, gold is the country's leading export resource before cotton and cattle with a total export volume of 2 billion US dollars in 2018, making the country Africa's third-largest exporter of gold behind South Africa and Ghana. While large-scale mining (LSM) produces most of the country's gold, another form of mining known as Artisanal and Small-scale Mining (ASM), exists alongside. Although the production quantities of ASM are lesser[1], they are a significant source of livelihood in Mali and there is still little evidence on the effect of this type of mining on child outcomes.

I implement the model proposed by Bazillier and Girard (2020), a difference-in-difference estimation, in which the treatment comes from variations in the global gold price and the distance to gold mines. I assume that gold price is exogenous (Mali is a price taker in the global market for gold)

[1] ASM accounts for approximately 10% of the total gold production as of 2011 (U.S. Geological Survey Minerals Yearbook).

and induce a time variation in gains from mining. I define the location of ASM and LSM sites by using GPS data on the location of registered small-scale and artisanal mines and large-scale mines, respectively. I construct a dataset that is a repeated cross-section by combining mining data with nationwide representative household surveys and child labour surveys from the Demographic and Health Survey (DHS) collected in 2001 (before the gold price increase) and 2012 (after the gold price increase).

The measure of gold price boom shows that child labour is pro-cyclical. That is, the gold price boom increases child labour in the vicinity of registered (legal) ASM. As in Kruger (2007) and Santos (2014), school attendance and school attainment is counter-cyclical. The estimates imply that a one percent increase in the price of gold increases the employment of children by 0.06%, in the vicinity of mines. Similarly, the probability of performing domestic chores increases by 0.03% for every one percent increase in the price of gold. As in Bazillier and Girard (2020), the results show that large-scale mines have no effect in my model.Furthermore, household characteristics, such as the presence of sisters for boys and the years of education of the head mitigate the impact of the gold boom. Ultimately, the main results suggests that the substitution effect dominates. As the price of gold rises, both child and adult labour become more profitable in the mining sector or any sector that is linked to the mining sector.

The contribution of this paper is three-fold. First, the analysis uses satellite imagery and detailed geographic information that allows to measure both LSM and ASM at a high-spatial resolution. I reduce the knowledge gap on the local impact of ASM as previous studies focus mainly on large-scale mining (Aragón and Rud (2016); Ahlerup et al. (2019); Kotsadam and Tolonen (2016); Axbard et al. (2019)). The increasing role of ASM in developing countries show that these operations must be taken into account in order to fully understand the local impacts of resource extraction. Second, I contribute to the literature on the cyclicality of child labour and human capital decisions by providing novel evidence on how these decisions may be affected by transitory positive shocks. Not much empirical evidence exists of the consequences of commodity booms on human capital and child labour decisions, especially using Malian data. Third, I contribute to the literature on the resource curse that documents a negative relationship between natural resources and education attainment (Gylfason, 2001).

The content of the rest of the chapter is organised as follows. Section 1.2 gives a brief background on the gold boom in Mali, the educational system, the impact of gold mining on schooling and child labour, Section 1.3 introduces the data and Section 1.4 presents the empirical strategy. Section 1.5 presents the results. Section 1.6 studies factors that mitigate the effects. Section 1.7 discusses the substitution effect as the key mechanism and tests alternative mechanisms through which gold mining could affect children outcomes and Section 1.8 is devoted to some robustness checks. Finally, Section 1.9 concludes.

1.2 Background

1.2.1 The gold boom in Mali

Mali has a long tradition in gold mining. However, gold production and exports have recently increased for two reasons: the introduction of a commercial mining code as part of the liberalisation process in the 1990s, and the upward trend of world prices, both of which have made production more profitable. Indeed, since the dramatic increase in the world price of gold in early 2000s, gold became Mali's largest export product, surpassing cotton: it represented around 400million FCFA of the exports in 2001 (the starting year of this study) and increased to around 900million FCFA in 2012 (the final year of the study) (Thomas, 2010). The price of gold increased by a factor of 6 between 2001 and 2012, from USD$271.19 an ounce to USD$1668.86 an ounce (see Figure 1.2). The mining sector is an important source of revenue for the government, which holds an equity position in all exploration activities with no financial

Figure 1.1: Location of Large-scale Gold mining sites, before 2013

Table 1.1: Gold production in Mali (1997-2012) (tons).

1997	1999	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
16.4	23.7	51.3	63.7	51.6	41.6	49.1	58.4	52.8	48.7	49.7	46.0	40.0	45.0

Source: Direction nationale de la géologie et des mines (DNGM), «Rapports de levées d'or des sociétés d'exploitation minière» and U.S. Geological Services,The Mineral Industries of Mali and Niger 2010-12.

contribution on their part. Mines also contribute to local development by engaging in community activities and building infrastructure, such as schools, hospitals, and roads, providing access to previously remote locations.

In terms of level, total gold production amounted to 16.4 tons in 1997, reached a high of 63.7 tons in 2002 and amounted to 45 tons in 2012 (Table 1.1). Although there has been increase in the employment in the large scale mining (LSM) sector, the job creation has been modest due to the capital-intensive and high-skilled nature of the sector.

1.2.2 Artisanal and Small-scale Mining (ASM)

While most of Mali's gold is produced by Large-Scale Mining (LSM), another form of subsistence mining operation more labour intensive, known as Artisanal

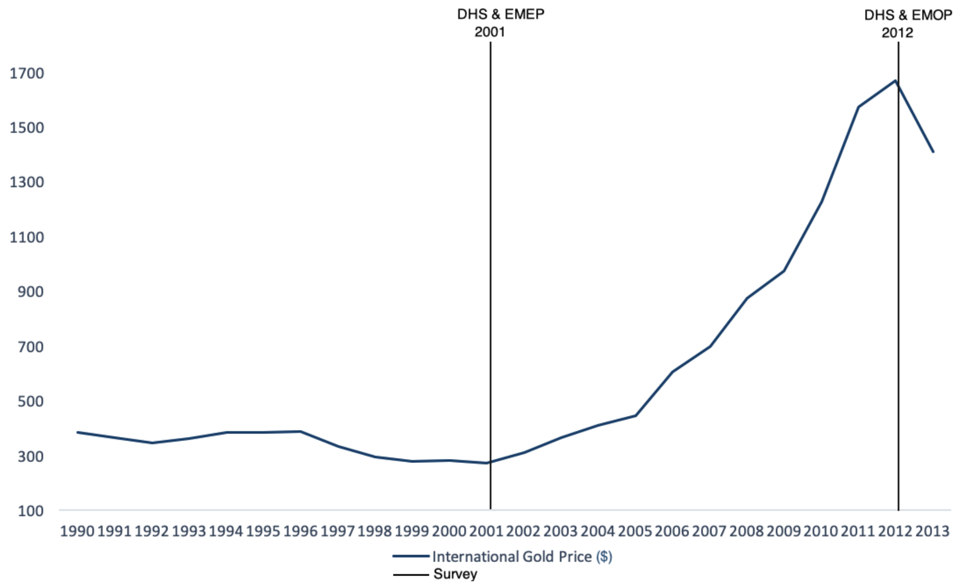


Figure 1.2: Evolution of International Gold Price (1990-2013)

and Small-Scale Mining (ASM), coexist in the country. ASM produces about 4 tons per year. ASM miners are not always officially employed by a mining company but rather work independently, using their own resources. They often combine mining with other activities such as agriculture and livestock breeding or informal activities in services and craftwork (Hilson, 2016). In Mali, ASM is found especially near large-scale mines, where residual lower grade ores are often left out by these big companies and further mined by artisanal miners. ASM may also be carried out in abandoned mining areas, tailing dams, or downstream areas.

ASM has strong linkages and spillovers with the local economy. For every one person working directly in ASM, up to five additional people are indirectly supported by work in associated industries and activities[2] (Bannock, 2005). These include more concentrated local commercial activities in the form of businesses such as taxi drivers, mineral traders, buyers and refiners, shops, bars, food stalls and restaurants, local markets, equipment suppliers and farming inputs. This multiplier effect often results in the local economies

[2]Data on ASM employment multipliers in developing countries are not available, the respective values are estimated for the U.S.A. and provide an indication.

of entire towns and communities being built around, and dependent on, the sector as their main source of livelihood.

The size of the sector fluctuates with the gold price and other employment opportunities. It is estimated that approximately 400,000 people are directly employed in ASM and 2.4 million people depend on it in some indirect way (Hilson, 2012). Given the importance of the sector, the Malian government attempts to regulate ASM by providing authorisations and permits to ASM operations. These artisanal mining authorisations are granted to Malian nationals and the exploitation license gives, within limits of a perimeter, an exclusive right of prospection, research, exploitation, treatment and marketing of gold. In return, local authorities receive payments of duties and taxes. ASM's operations can be performed by individual miners as well as by cooperative companies.

This study provides estimates of the impact of artisanal and small-scale mining by using data on the ASM permits published by the Minister of Mines of Mali. This enables me to account for the presence of both a large-scale mine and ASM and estimate their effects on local communities. However, given the high level of informality of ASM, the sector remains difficult to regulate and very often is carried out illegally. This makes it difficult to give an accurate estimate of each location and involved parties of ASM and hence could imply that my estimate of ASM sites could be underreported.

1.2.3 Schooling in Mali

There are three types of education in Mali: Community schools that rely mainly on village communities and NGOs, private schools and public schools that depend on the state. All public schooling in Mali is provided free of charge and legislated as compulsory for children between 7 and 16 years old. The system comprises of six years of primary education directly followed by another six years of secondary schooling (Hilson, 2012). Empirical evidence has shown that Mali's education system is subject to high rates of delay in schooling of children and girls in particular. This is explained by high ancillary education costs, including transportation, purchases of writing supplies and uniforms, which represent a major financial sacrifice in a country where more than half of the population lives in poverty (UNDP, 2012). Often families choose to send only one or two of their children to school, the choice is then more often on boys, accentuating the gender gap (Hilson, 2012). The educational system is hindered by a lack of resources (infrastructure, textbooks and staff), overloaded classes and frequent dropouts (Hough, 1989). Another shortcoming of the system is the inequity of access to primary and secondary education for rural and urban populations, due to a concentration of schools in urban areas. All of which leads to school attendance rates that do not exceed 25% in some regions of the country (Diané Baba, 2015).

1.2.4 Literature review: Impact of a gold mining boom on child labour and schooling

The model in Basu and Van (1998) assumes that children's leisure is a luxury good, which poor households can only afford if income rises. Therefore, one channel through which a gold mining boom could impact education, could be through an increase in household income. Mining employment, especially in ASM, could represent a significant and higher source of income relative to farming activities for poverty-driven population and rural communities, who usually suffer from limited job opportunities (Hilson, 2009). These increased revenues could allow families to afford education costs.

Another channel that could lead to higher levels of education is an increase in public spending, provided that local institutions are healthy (Land, 2015). The revenues the mining sector contributed to local institutions could serve to improve the supply and the quality of public goods and services such as electricity provision, water source, roads and schools, and thus improve education outcomes. Guarcello et al. (2004) showed that access to electricity and water source could reduce the value of children's time in non-schooling activities. Children become less needed to assume the responsibility of water collection or no longer are required to help cover the cost of buying water (Guarcello et al., 2004). An improved source of energy for lighting could also influence the time children need for collecting wood. Furthermore, the construction of schools creates access for children to attend classes and hence raise school attendance (Kondylis and Manacorda, 2012).

However, another strand of the literature documents that child labour and income shocks behave in a pro-cyclical manner. That is, by increasing the opportunity cost of education, higher income gains influence parents to send their children to work for subsistence rather than going to school. Beegle et al. (2006) discovered that a transitory shock in crop prices in Tanzania is associated with a 30% increase in child labour. In this same line, Kruger (2007) shows how the education of poor and middle-income children is negatively impacted in the periods of economic growth in coffee-producing regions of Brazil. Cogneau and Jedwab (2012) examine this mechanism, focusing on cocoa prices in Ivory Coast and indicate that positive price shocks increase child labour incidence.

In the context of natural resources, Santos (2014) shows the repercussions of a gold boom on child labour and school attendance in Colombia. According to that paper, a one standard deviation increase in the gold mining boom reduces school attainment by 0.07 standard deviations. Zabsonré et al. (2018) find similar effects of gold extraction on schooling and child labour using the approach in Loayza and Rigolini (2016) for the case of Burkina Faso. Using 166 countries, Gylfason (2001) finds a negative relationship between natural resource wealth and school enrollment.

The spillovers arising from the gold mining boom, particularly in the context of weak local institutions, could negatively affect education by increasing rent-seeking opportunities (Land, 2017). This may in turn generate higher corruption and conflict. An increase in conflict intensity could lead to a drop in household consumption and thus increase the participation of children in work activities since households may want to use child labour to insure against the decreased consumption (Kofol and Ciarli, 2017). Education may also be adversely affected if families are displaced due to higher conflict intensity (Smith et al., 2003).

Furthermore, gold mining activity could be detrimental for children's schooling if the rise in local labour demand and increased nominal wages from a gold mining boom attract workers from other cities. This increased population could cause congestion in public services, such as education (Land, 2017). Loayza and Rigolini (2016) argue that the type of people that gold mining attracts could also affect education's outcome. If gold mining induces migration from more skilled workers, thus increasing the share of more educated workers in mining areas, the outcomes on education could only reflect changes in the composition of the population rather than real improvements in economic welfare.

1.3 Data

I construct a repeated cross-sectional data set using various sources. These include (i) child labour data from two rounds of the Demographic and Health Surveys (DHS) of Mali; (ii) two rounds of nationwide representative household surveys; (iii) geocoded Mining data on LSM and ASM sites from Infomine and the Direction Nationale de la Géologie et des Mines (DNGM) in Mali.

1.3.1 Demographic and Health Surveys (DHS)

First I use micro data from the Demographic and Health Surveys (DHS), which uses household questionnaires to collect comprehensive information on children's activities in Mali, that are suitable for this analysis. An important benefit of the DHS is that the groups of households taking part in the surveys, identified as clusters, are georeferenced. In other words, they are associated to a ground system of geographic coordinates, which allows me to calculate a proxy for the distance between households and gold mines and assign them to treatment or the comparison groups[3]. This study makes use of two rounds

[3]In order to ensure respondent confidentiality, the DHS follows displacement procedures in which it randomly displaces the GPS latitude/longitude positions for its surveys. The spatial coordinates for urban locations are displaced by 0-2 km. Rural locations as well as

for which this information is available, 2001 and 2012. To the best of my knowledge, this study is the first to construct such an extensive dataset and exploit the geocoded child labour data, in the context of Mali.

For the purpose of this study, I define the age of a child to be between 7 and 14 years. This coincides with the starting age of school in Mali and will not mislead the results on school enrolment. Economic participation is a dummy that takes the value of one if in the week preceding the survey, the child worked for someone outside the household (paid or not), worked for a household business (paid or not) or worked on the farm. Domestic participation equals one if the child performed domestic chores such as cleaning the house and preparing meals, over the past week. Domestic participation is included for two reasons. First, child labour is not restricted to economic activities. Second, in rural areas it may be difficult to distinguish between time spent on household chore activities and time spent preparing subsistence food crops.

Attended school is defined as one if the child attended school a week prior to the survey. Akin to Santos (2014), school attainment takes the value of one if the child has attained the school grade she should be in, given a normal progression in school. School lag is a dummy that is equal to one if the child is three or more grades below her expected grade. School attainment and school lag are used as proxies for educational achievement, although it is recognised that such measures cannot fully reflect school performance. Since the surveys represent a point in time, they cannot account for the cumulative effect of child labour on attainment over time.

1.3.2 National Household Surveys

One limitation of the DHS data is that they do not collect information on economic measures of poverty, such as income or expenditure. I complement the analysis with nationwide representative household surveys. In the follow-up of policies to fight against poverty, the government of Mali initiated the conducting of a series of surveys, aimed at collecting a wide range of socioeconomic

an additional 1% randomly selected clusters are displaced up to 5 km.

indicators needed to monitor and evaluate improvement in households' living conditions. More specifically, the EMEP (Enquete Malienne d'Evaluation de la Pauvrete) conducted in 2001 and the EMOP (Enquete Modulaire et Permanente Aupres des Menages) in 2012, were designed to update the indicators of the Growth and Poverty Reduction Strategic Framework (GPRSP) in line with those of the Sustainable Development Goals (SDGs). The information collected includes household expenditure, which has been argued in the literature to be a good indicator of household welfare as opposed to income, because of its stability (Grimm and Gräb, 2011). The assumption being that higher consumption expenditure per head of household, increases the household's ability to satisfy its vital needs. Also, Brewer and O'Dea (2012) argue that income in household surveys is usually under-reported for households with low resources. To obtain a real measure of expenditure per capita, the nominal values are deflated using an indicator of household poverty status.

1.3.3 Gold Mining Data

The Mining data come from several sources. Infomine, provided a dataset containing the geocoded location of Mali's main large-scale gold mines from 1990 to 2012. Information on their production levels comes from the Direction Nationale de la Géologie et des Mines (DNGM) of Mali and the US Geological Survey (USGS). Regarding Artisanal and Small-scale Mining (ASM), I obtain the location of registered artisanal and small-scale mines by the Ministry of Mine of Mali. Though the list they provide is the best data to date on ASM, it does not include every place where ASM is taking place. This could cause a potential attenuation bias in the results. The dataset I construct consists of 7 large-scale gold mines and 13 ASM sites across the country.

1.3.4 Descriptive Statistics

Table 1.2 reports the summary statistics for the main variables of interest. It computes the means and standard deviations and includes the figures for the sample area[4] and households with full observations. I observe that 60% of children are not enrolled in a schooling program and 39% participate in economic activities. Mali is known to have one of the highest fertility rates in the world, looking at the data, the average household size is 9 members and the average number of children (aged 7-14) in a household is 5. The children in the DHS sample are on average 10 years old and have 1.30 years of education. With regards to access to facilities, around 19% of households have access to drinking water and 13% have access to electricity. The average distance to a LSM site is 88 km and 90 km to an ASM site. In terms of household consumption, expenditure per capita per district is on average 36382 CFA, which is approximately 60 USD[5].

Table 1.2: Descriptive Statistics

	Mean	Std. Dev.	Obs
Economic Participation (%)	39.41	0.49	10374
Economic Hours (per week)	8.10	19.47	10374
Domestic Participation (%)	61.33	0.49	10374
Domestic Hours (per week)	10.81	16.20	10374
Attended School (%)	40.31	0.49	10374
School Lag (%)	12.74	0.33	10374
School Attainment (%)	74.97	0.43	10374
Real expend. per capita	36381.67	14303.56	10374
Education (years)	1.30	2.72	10374
Age	10.25	2.30	10374
Male (%)	50.59	0.50	10374
Male (Head)	90.96	0.29	10374
Age (Head)	49.62	12.32	10367
Literate Head (%)	38.28	1.05	10329
Rural (%)	85.67	0.35	10374
Electricity (%)	13.04	0.34	10374
Access to Water (%)	18.55	0.39	10374
Household size	8.82	3.80	10374
Number of Kids (7-14)	5.43	2.82	10374
Distance to LSM Site (km)	88.28	54.46	10374
Distance to ASM Site (km)	90.07	54.80	10374
Mining Deforestation (Ha)	0.24	0.57	10374

[4] I restrict the sample to the three regions in which I identify gold mines, Kayes, Koulikoro and Sikasso.

[5] The CFA Franc has a fixed exchange rate with the euro (656 CFA Francs= 1 euro).

1.4 Empirical Model

The aim of the paper is to evaluate the effect of gold mining on child labour and schooling. To identify the effect of mining, two sources of variations are exploited: the boom in the international price of gold, which provides with a time varying treatment, and the household's distance to gold mines, which serves as a heterogeneous exposure to the mining spillovers. This identification strategy is thus a difference-in-difference based on spatial and time variations.[6] This section explains how this strategy enables me to identify the effect of artisanal and small-scale and large-scale mining.

I identify the locations of artisanal deposits by using the census of artisanal mines registered at the Ministry of Mines. In my baseline specification, I use a 10-kilometre buffer to distinguish treated and non-treated households (I present alternative distance definitions in my robustness checks). With regards to large-scale mines, I also exploit difference in time and spatial variations. Similarly to ASM, the spatial source of variation is the household distance to a gold deposit, as a source of heterogeneous exposure to a potential mine. Here, I use a 20-kilometre buffer to divide treated and untreated households.[7] The boom in the international price of gold provides a time-varying treatment. More specifically, I define P_t as the log of gold price. The rationale is that gold price should affect areas with high potential for gold mining more as it is the main driver of mining activities and directly defines the expected benefits of the miners. When the price of gold increases, a substitution effect in which households may favour shifting, diversifying activities or increasing their labour supply to gain from new income opportunities, may take place.

[6] The strategy mirrors that of Bazillier and Girard (2020) and is based on a household and individual level approach. Unlike this study, the main outcomes of focus in Bazillier are consumption patterns, they author show that the gold boom generates an increase in consumption for households located close to artisanal mines. However, they also briefly look at human capital outcomes and find that the gold boom in Burkina Faso has not affected health and education, either for artisanal or for industrial mining.

[7] The literature uses several distance definitions. I choose this threshold taking into account that LSM sites are bigger than ASM and the demand shock is prone to be less concentrated. Nonetheless, I use alternative distance definitions in robustness checks.

Due to the repeated cross-sectional nature of the dataset, the identification strategy is a difference-in-difference based on spatial and temporal variations. I focus on the Demographic and Health Survey (DHS) and nationwide representative household surveys to combine geocoded household enumeration areas with the location of large-scale and small-scale and artisanal mine sites to construct the treatment group. In the baseline specification, children are assigned to the treatment if their household enumeration area is within 10km of an ASM site and/or 20km of a LSM site. The main assumption of the difference-in-difference is the parallel trend. In other words, I assume that the evolution in children outcome indicators far and close to these mines, from the baseline to the post-treatment period, would have been similar for all units of observation in the absence of the increase in gold mining activities.

I estimate the following specification to evaluate the effect of LSM and ASM on children outcome:

$$
\begin{aligned}
Y_{idt} = \beta_0 + \beta_1 ASM\_area_d + \beta_2 Price_t + \beta_3 (Price_t \times ASM\_area_d) \\
+ \beta_4 (Price_t \times LSM\_area_d) \\
+ \beta_5 (LSM\_area_d) + \phi X_{it} + \alpha_d + \epsilon_{idt} \quad (1.1)
\end{aligned}
$$

where Y_{idt} is the outcome variable of child i in district d in year t. This outcome variable depending on the regression corresponds to either local employment or an outcome of interest for children. ASM_area_d is a variable measuring the treatment and is equal to 1 if household is located within 10 km of an ASM site and 0 otherwise. LSM_area˙d is equal to 1 if the household lives within 20 km of a large-scale mine, 0 otherwise. I include an interaction between the gold price and the large-scale mine dummy since a high gold price translates to more profit for mines. The first coefficient of interest, β_3, shows the impact of the change in the gold price on child labour and schooling of children who live within 10 km of an ASM gold mining site. The second coefficient of interest, β_4 estimates the impact of the change in the gold price for children who live within 20 km of an LSM site. Specification (1.1) is estimated using a pooled cross section of two years, 2001 and 2012. One year is the pre-treatment year and the other one is the post-treatment year. I include, α_d, district dummies to control for any district fixed effects and a vector of household and individual characteristics, X_{it}. These include age, sex and literacy of the child, household head, and parents, the number of household members and a dummy for household living in rural areas. I also add a dummy on whether the mother and father of the child have worked in the past twelve months, electricity and water supply.

Table 1.2 gives details on the full set of control variables. The regression is estimated using sample weights and the standard errors are clustered at the district level to account for serial correlation at this level. The empirical methodology is illustrated in figure 1.3. The concentric circles around mining sites are catchment areas for the treatment group and the clusters outside the catchment area are the comparison group. Note that all mines are located in three regions: Sikasso, Koulikoro and Kayes. In the empirical section, the sample is restricted to these regions.

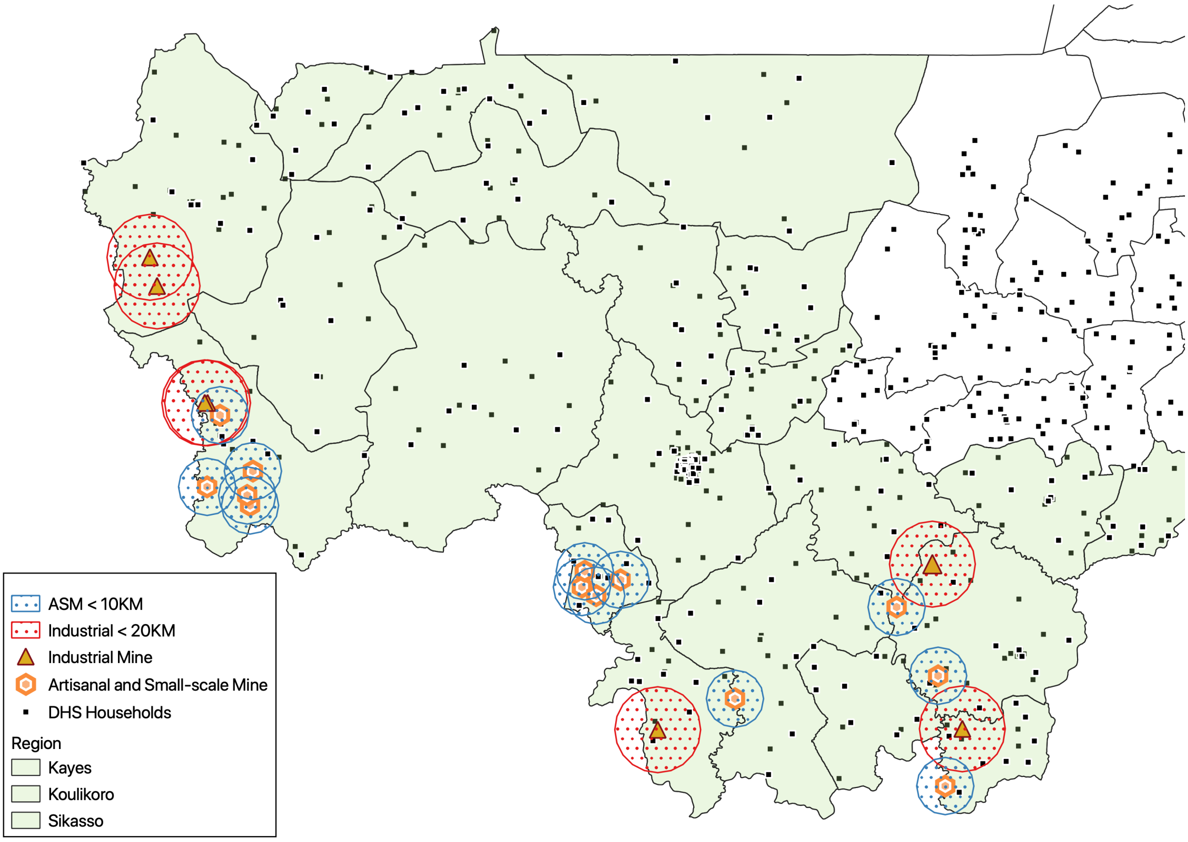


Figure 1.3: Location of Mines and DHS Clusters

1.5 Results

Table 1.3 reports the results of estimating equation (1.1) by OLS. All specifications include individual and household controls as well as time and district fixed effects. Column (1) uses economic participation as the dependent variable. The artisanal gold boom variable, measured by the interaction of the international gold price and area within 10 km of an artisanal sites is positive and significant at the 5% level. Table 1.2 shows that a one percent increase in the gold price increases the employment of children in the vicinity of mines by 0.06%. Similarly, the probability of performing domestic chores increases with the measure of artisanal mining. In fact a one percent increase in the gold price increases domestic chores by 0.03%. The results of the gold boom on school enrollment are insignificant (column 3) for children aged 7 to 14 years old. However, columns 4 and 5 show that the mining expansion has a significant negative and larger effect on children's academic performance. The mining expansion is correlated with less school attainment. A one percent increase in the gold price decreases children's school attainment (the probability that a child has attained the school grade she should be in, given a normal progression in school) by 0.03%. Similarly a one percent increase in the price of gold increases the school lag (the probability that a child is three or more grades below her expected grade) by 0.04%. The coefficients for school lag and the school attainment are larger and more statistically significant than current school attendance. This could be because both of these variables reflect the cumulative effect of a child not going to school over the last few years. This is likely to have adverse effects on welfare given the positive and permanent effect of years of education on wages.

The impact of the mining activity on child labour and education may be non-uniform, in the sense that the gender of children may influence the allocation of child labour activities differently. This is especially likely in a developing country like Mali where men and women usually participate in different economic activities (Bhat,2010)[8]. To further examine this, I estimate the regressions by separating the results by children's gender. Table A.1 in Appendix A presents the results. I observe that the ASM activity impacts on the extensive margin of male child labour. The adverse impact on school attainment and school lag is driven exclusively by female children. There is a substitution in the participation in domestic chores to economic work for males, induced by the increase in gold price. This also translates in the number of hours of labour as shown in Table A.2. The different experiences of girls and boys highlight the importance of integrating gender concerns into child labour research and policies.

[8]Usually, when women are employed, they tend to occupy functions that are related to their domestic role such as nursing, cooking, teaching, cleaning, providing clerical support, etc.

Table 1.3: Gold Boom effect on Child Labour and Schooling

	(1) Economic Work	(2) Domestic Chores	(3) Not attending	(4) School Attainment	(5) School Lag
Price	0.138***	-0.149***	0.0015	0.0553***	-0.0261***
	(0.0138)	(0.0144)	(0.0080)	(0.0072)	(0.0045)
Price× ASM Area	0.0587*	0.0278*	-0.0257	-0.0287**	0.0379***
	(0.0253)	(0.0211)	(0.0274)	(0.0106)	(0.0088)
Price× LSM Area	-0.0916	0.0607	0.0116	0.0176	-0.00162
	(0.0635)	(0.0321)	(0.0210)	(0.0167)	(0.0133)
ASM Area	-0.444**	0.151	0.205	0.159*	0.247***
	(0.166)	(0.134)	(0.155)	(0.0673)	(0.0546)
LSM Area	0.677	-0.378	-0.0958	-0.114	0.0205
	(0.430)	(0.215)	(0.129)	(0.105)	(0.0816)
Male	0.0413*	-0.247***	-0.0372***	-0.00118	-0.00702
	(0.0172)	(0.0155)	(0.0077)	(0.0069)	(0.0060)
Age	0.156***	0.0845***	-0.187***	-0.00046	-0.0815***
	(0.0224)	(0.0250)	(0.0182)	(0.0208)	(0.0188)
Age^2	-0.0055***	-0.00278*	0.0104***	-0.0019	0.0064***
	(0.0011)	(0.0012)	(0.0009)	(0.0010)	(0.0009)
Rural	0.112***	0.0420	0.0491**	-0.0259	0.00485
	(0.0329)	(0.0373)	(0.0161)	(0.0180)	(0.0159)
Electricity	-0.0770**	-0.0182	-0.0389**	0.0377*	-0.0271
	(0.0276)	(0.0271)	(0.0147)	(0.0162)	(0.0142)
Water	-0.0680**	-0.0282	0.0075	-0.00545	-0.0083
	(0.0252)	(0.0294)	(0.0124)	(0.0148)	(0.0100)
Household size	-0.0140**	-0.0136**	-0.00372	-0.00188	0.0018
	(0.0046)	(0.0046)	(0.0020)	(0.0025)	(0.0019)
N	10374	10374	10374	10374	10374

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include district and year fixed effects, and individuals and households' controls, which include: individual's age and gender, household head's age and gender, literacy, asset, size, access to water and electricity; as well as an indicator of the household area.

1.6 What factors mitigate the negative effects of the Gold Boom?

Do households spread the labour across children?

Larger families may facilitate schooling, at least for some children. If the utility of the household increases with education, then it might be the case that households mitigate the impact on education by sharing the work duty and responsibility across children. There may be a sort of specialisation in the household, whereby some children work, while their siblings don't and are permitted to attend school and concentrate on studying. This section tests this assumption, according to which households may want to spread the burden of labour across children.

To explore this, I first look at the sibling composition in a given household and interact the treatment variables with a dummy variable that takes the value 1 if the child has no siblings and 0 otherwise. One issue with this, however, is that the number of people in a household is endogenous and can therefore not imply causation. To overcome this issue of endogeneity, I interact the treatment variables with being the eldest child, as the birth order is considered to be random. Indeed, older children may have felt the burden of child labour more since at a point in time, when they were young, there were no other children in the household available to work to help supplement family income. Also, one could believe that the presence of younger siblings could increase the demand for childcare and hence impose a burden on school enrolment. In addition to birth order, the sibling gender composition may also be important. For example, parents may be more altruistic toward a gender, usually sons relative to daughters, in traditional societies, thus creating differences in household resource allocation, including in education. I examine this by interacting the treatment variables with having a sister.

Tables A.3, A.4, and A.5 in Appendix A report the results. Even though the signs of the treatment effects tend to support the argument that children with no siblings and eldest children have a lower probability of attending schooling, the results are insignificant. However, Table A.5 shows that with regards to the gender of their siblings, boys with a sister are expected to be less involved in household chores. If boys have a sister, the household tasks are distributed among their sisters' helping hands. The results also show that having a sister is beneficial to boys educational attainment as they see their educational attainment increase by 14%. Having a sister has no significant effect on girls. This points to higher investments in sons and hence favours the hypothesis according to which households spread the burden of labour across children in the vicinity of mines.

Do the years of education of the head of household matter?

Households in which the head has a higher education level than the sample average may be more likely to recognise the value of education and to send the children to school. Moreover, they are also more likely to have higher incomes, which would give them the means to afford education for the children in their household. Table A.6 in Appendix A indeed shows that increased educational level of the household head is linked to increased school attendance rates of children. While the effect of the measure of surging world price of gold in ASM area on not attending was insignificant, it is now negative and significant at 5% for the head with more than the average years of education. I estimate the probability not to attend school to decreases by 9% for the households in which the head has a higher education level. The number of years of education of the head may thus capture preferences for education (or a measure of income).

1.7 Mechanism: The Substitution effect

In line with previous studies such as Mejía (2020), Ahlerup et al. (2019), Zabsonré et al. (2018) and Santos (2014), the results reported above show that the surge in the international price of gold generates a positive effect on child labour and a negative effect on educational attainment. As a consequence, this might have influenced the prices and costs available when parents decide to invest in their children.

As the price of gold rises, both child and adult labour could become more profitable in the mining sector or any sector that is linked to the mining sector. Under the assumption of imperfect local labour markets, child and adult opportunity costs may differ in households near mines compared to other households. Households near mines may give up leisure and increase their labour supply because work has now a higher reward. As a consequence, a price-induced increase in child labour could be indirectly detrimental for schooling outcomes; similarly, a price-induced decrease in adult leisure could reduce time for child care in households located in the vicinity of mines. In other words, the surge in the international price of gold could generate an economic boom in places suitable for producing gold, resulting in substitution effects that may be non-negligible in this setting.

To test this assumption, I regress household-unit level general non-employment, expenditure per capita and head of household employment against the measures of gold boom. The non-employment measures use information of all individuals recorded in the survey. Results are reported in Table 1.4. As the survey does not provide the hours worked by adults, I focus solely on the labour participation. The results show that the measure of mining activity is associated with an increased economic activity at the survey level, within 10km of an ASM site. In terms of magnitude, a one percent increase in the price of gold decreases non-employment by 0.008%. Column (3) is in line with these results as it shows that as gold prices increase, the probability that the head of household works is higher for households located within 10km of artisanal and small-scale mines than households located further away.

The results also show that a one percent increase in the gold price increases the households' expenditures by 0.20% for households living within 10km of a registered artisanal and small-scale mine. However, the negative sign in front of ASM area shows that these areas have a higher probability of non-employment and are poorer compared to other areas far away. The increase in international gold prices thus generates more economic opportunities and higher standard of living in ASM area. The results show no significant effect of LSM on the outcomes.

Table 1.4: Gold Boom effect on the share of non-employed Head and Expenditure per capita

	(1) Share of Not working (All)	(2) Share of Not working (10-35)	(3) Household Head working	(4) Ln Expenditure per capita
Price	0.0319***	0.0304***	-0.0655***	-0.0013***
	(0.0026)	(0.0028)	(0.0181)	(0.0004)
Price × ASM Area	-0.0083**	-0.0078**	0.0589***	0.196***
	(0.00281)	(0.00276)	(0.0155)	(0.0120)
Price × LSM Area	-0.0223	-0.0214	-0.0325	0.0272
	(0.0176)	(0.0179)	(0.0437)	(0.0390)
ASM Area	0.0521**	0.0488**	-0.290***	-1.281***
	(0.0169)	(0.0166)	(0.0807)	(0.0911)
LSM Area	0.128	0.123	0.207	-0.236
	(0.100)	(0.102)	(0.255)	(0.271)
N	15678	12643	10374	10374
R^2	0.27	0.29	0.18	0.23

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include district and year fixed effects, and individuals and households' controls, which include: individual's age and gender, household head's age and gender, literacy, asset, size, access to water and electricity; as well as an indicator of the household area. The non-employment measure uses information of all individuals recorded in the household survey (children and adults).

1.7.1 Alternative mechanisms

In this section, I investigate three alternative mechanisms through which gold mining could affect children outcomes and assess to what extent they can explain the baseline findings. The first set of results focuses on public investment, such as the provision of schools and other public goods that can potentially affect children. Secondly, I look at returns to education. I finally assess the effect on endogenous migration.

1.7.1.1 An alternative channel: Provision of Public goods

The gold mining activity can be considered as a source of fiscal revenue for local communities (Aragón and Rud, 2013) and may have an effect on schooling attainment if the government is able to support higher public spending such as school provision, in mining districts. However, the local authorities may believe that children in mining areas have more and easier employment opportunities in mining sector and are thus less in need of an education. Likewise mining operations could affect local water endowments and cause severe deterioration that would increase the value of children's time in non-schooling activities and thus increase the child labour rate. Parents may find optimal for their children to spend more time on household chores (e.g. fetching water, food, cooking, etc.) obliging them to allocate less time to other activities such as schooling.

I explore the importance of this transmission channel by relating the presence of gold mines to the provision of public goods. If governments provide less public goods to districts with mines, we should observe a negative correlation between gold mining activity and public goods provision. One way of testing this channel is to control for the presence of schools in the vicinity of mines. However, the DHS does not provide such data. To find this information I use a map from the Humanitarian Data Exchange (HDX) that points the location of each school facilities across the country. I check for the presence of a school within easy walking distance (2 kilometres, see Figure 1.4) of the household in the year of the survey. I also control for the presence of electricity and access to a water source, which are good proxies for public infrastructure especially in developing countries, where the government usually acts as the sole provider of these services. Table 1.5 shows no evidence that children in the proximity of mines have less schools and electricity grid. In fact, they have better access to drinking water sources and could thus spend less time fetching water. This result is similar to Sanoh and Massaoly (2015) who highlight that Malian gold mining communes made significant progress in water provision from the period 1998 to 2009. Columns (4) to (8) control for the presence of public goods by adding schools as covariates. The inclusion of this variable does not impact the probability of school attendance and increases the overall probability of child labour participation. In line with Ahlerup et al. (2019), this suggests that the effect of gold mines on children outcome cannot be explained by under investment in schools from local authorities.

Figure 1.4: Map of School Locations

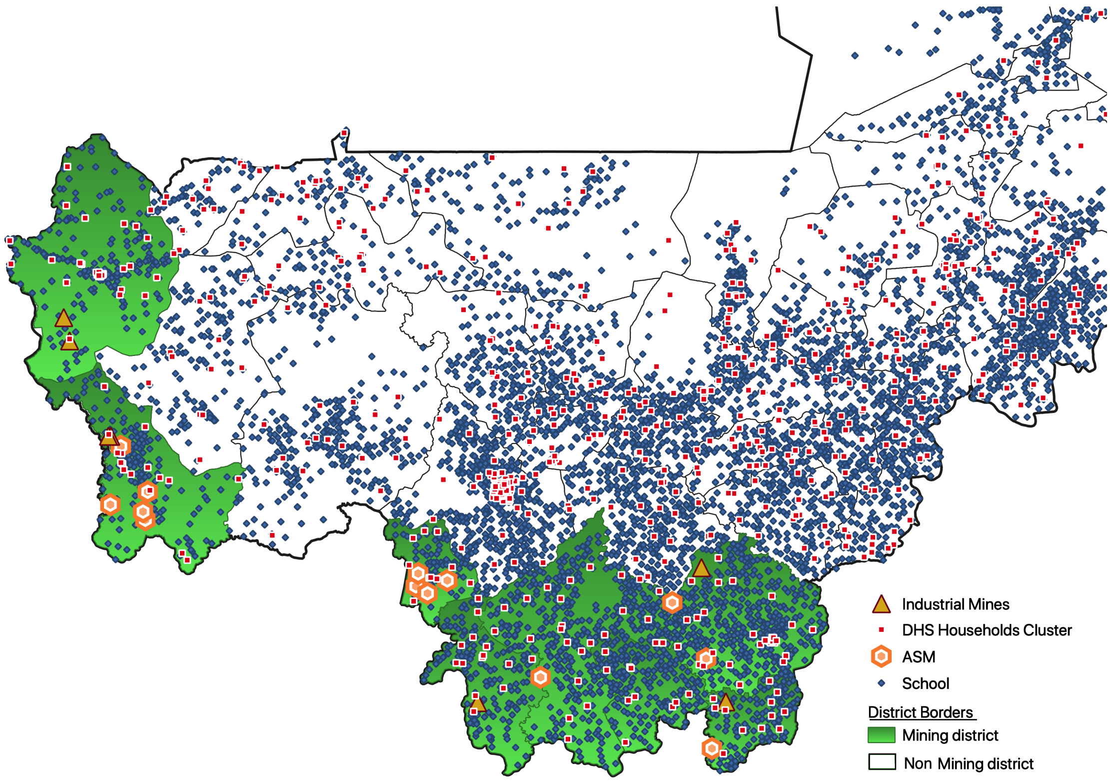


Table 1.5: Effects of Mining on Public goods

	Public goods			Control for Schools				
	Elec	Water.	School	Economic	Domestic	Not attend.	School Attain.	School Lag
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price	0.0878***	0.214***	-0.0215	0.425***	-0.513***	0.0092	0.0168***	-0.0694
	(0.0203)	(0.0192)	(0.0418)	(0.0324)	(0.0322)	(0.0026)	(0.0132)	(0.0067)
Price × ASM Area	-0.104	0.049***	-0.247	0.0628***	0.0289**	-0.0239	0.00141	0.0438**
	(0.0267)	(0.0849)	(0.193)	(0.0353)	(0.0308)	(0.0282)	(0.0155)	(0.0100)
Price × Ind. Area	-0.0678	0.0959***	0.297*	-0.0104	-0.0377	0.0109	0.0477	-0.0159
	(0.0360)	(0.0532)	(0.145)	(0.0691)	(0.0403)	(0.0202)	(0.0216)	(0.0146)
ASM area	0.485**	0.331	2.054	-0.447***	0.172*	0.192	-0.454	0.356***
	(0.165)	(0.479)	(1.108)	(0.228)	(0.196)	(0.160)	(0.0970)	(0.0628)
Ind. Area	0.431	0.563	-1.777	0.152	-0.249	-0.0913	-0.309*	0.113
	(0.230)	(0.304)	(0.959)	(0.463)	(0.261)	(0.124)	(0.135)	(0.0901)
School				0.0126	0.0395	0.00451	0.0138	-0.0101
				(0.0299)	(0.0251)	(0.0114)	(0.0117)	(0.00767)
N	10101	10101	10101	10101	10101	10095	10101	10101
R^2	0.26	0.34	0.25	0.12	0.15	0.45	0.45	0.41

Notes: Robust standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include year and district fixed effects and control for household head's education, age, gender and dummies indicating her industry of occupation and type of job. Also access to water and electricity, the size of household and an indicator for rural household. Gold Production is measured in tonnes.

1.7.1.2 An alternative channel: Returns to education

In this section, I consider the possibility that the relative returns to education influence child labour and schooling decisions. While estimating returns of schooling poses a challenge as many households are engaged in farming with wages that are not directly observed, Edmonds (2008) proposes to study behaviours that rely on the return to education instead of directly measuring the return. Following this strategy, I first compare the differences in per capita expenditure between skilled and unskilled workers by estimating the baseline regression by household head's education level. I define educated head as the ones showing literacy level, i.e., they are able to read and write. The idea behind this is to check whether the resource boom is biased towards low-educated head relative to higher-educated head. In which case, it could decrease the returns to education and hence increase the demand for child labour and influence the schooling outcomes in the vicinity of mines. The results, displayed in columns (5) and (6) in Table 1.6, show that the increase in real expenditure is positive and statistically significant for both educated and non educated head of households. However, the effect is doubled for more educated head of households. Greater expenditure for the more educated represent higher productivity and hence, an increasing return to education.

Second, I examine changes in adult employment by education status and distinguish heterogeneous effects on head of households employed in four main sectors (Agriculture, Mining, Sales, and Services) in the four regions that represent approximately 75% of the labour force. Columns (1) to (4) in Table 1.6 display the results using the whole sample and restricting it to agricultural, mining, sales and services workers. Results show that the ASM measure of mining activity leads to an increase in per capita expenditure among the workers in each of these industries. These results are consistent with a local employment shift created by the mining activity and inducing positive direct effects in the mining industry and indirect effects in agriculture and in other non-traditional sectors such as services and sales.

Table 1.6: Effects of Mining on Expenditure by Head Industry and Literacy

	Ln (real expenditure)					
	By industry				By education	
	(1)	(2)	(3)	(4)	(5)	(6)
Price	-0.552***	-0.494***	-0.506***	-0.494***	-0.503***	-0.475***
	(0.0118)	(0.0121)	(0.0126)	(0.0121)	(0.0125)	(0.0172)
Price × ASM Area	0.0658*	0.186*	0.195**	0.096**	0.223***	0.101***
	(0.0305)	(0.0120)	(0.0126)	(0.0120)	(0.0124)	(0.0448)
Price × LSM	-0.0126*	-0.0203	-0.00973	-0.0203	-0.0156	-0.143**
	(0.0360)	(0.0357)	(0.0364)	(0.0357)	(0.0345)	(0.0489)
ASM Area	-0.461*	-0.128***	-0.206***	-0.149***	-1.149***	-1.513***
	(0.211)	(0.0750)	(0.0793)	(0.0750)	(0.0750)	(0.306)
LSM Area	-0.0808	0.0750	0.00960	0.0750	0.0549	0.873**
	(0.224)	(0.227)	(0.231)	(0.227)	(0.213)	(0.298)
Sample	Agric.	Mining	Services	Sales	Educated	Non Educated
N	4490	4490	4490	4490	4490	4490
R^2	0.31	0.32	0.31	0.31	0.34	0.33

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include district and year fixed effects, and individuals and households' controls, which include: individual's age and gender, household head's age and gender, literacy, asset, size, access to water and electricity; as well as an indicator of the household area.

1.7.1.3 An alternative channel: Endogenous Migration

An interesting outcome in Mali is the differential population growth in mining compared with non-mining areas. In the two most recent population censuses, Sanoh and Massaoly (2015) noticed that the population in mining communes grew almost double than the national growth rate at around 6% between 1998 and 2009. Mining communes grew on average 5.7 percent annually, compared with 3.5 percent for neighboring communes and other communes within the same district (See Appendix A Figures A.1 and A.2). While the validity of the results on the evolution of children outcome depends on the assumption that the gold Boom had distinctive impacts across mining and non-mining areas, this is not necessarily true as wage differentials often induce population flows within a country. One potentially important channel is that the mining activity may attract individuals from other regions who are in search of employment. The migrant population may have lower standards of living and a higher child labour rate among children. That is, gold mining districts may have a higher share of less fortunate and less educated inhabitants, who choose to send their children to work more than the natives. Not because inhabitants opt to acquire less education but because poorer and less educated individuals are more likely to migrate into gold mining districts.

I have no information where the migrant population moved from, and I cannot tell whether they have migrated to the area (to benefit from the employment boom) or whether they were part of a relocation program due to the mining.

Ahlerup et al. (2019) explore this issue by matching respondents' self-described ethnic group to data on the native homelands of African ethnicities according to Murdock (1959). The idea is that respondents who belong to one of the native groups of the district are less likely to have migrated due to the presence of mines while respondents with a non-native ethnicity are more likely to have done so. Thus, by focusing on whether a respondent belongs to the native ethnic group they rule out, to some extent, this alternative interpretation. However, I recognise that at a country-level study this method does not rule out endogenous migration as it fails to identify that relatively unfortunate natives migrate within the country from non-mining to mining districts.

Aragón and Rud (2013) explore this issue by evaluating whether the mining activity has led to changes on observable characteristics of the labour force in mining and non-mining areas. They focus on different measures of human capital such as years of education, an indicator of having completed primary school, and an indicator of the worker being a male between 20 and 40 years old. Relying on this strategy, Table 1.7 shows the results of a test on significant differences in observable characteristics between adult male and female in the sample. In all cases, the baseline regression (1) is estimated with year and district fixed effects as the only control variables. I find that the estimates are not significant, i.e. that the mining activity has not induced any significant change in observable characteristics. These results are in line with Land (2017) and reinforce the argument that the findings have not been driven by migration of more educated households to mining areas, or different trends based on some observable characteristics.

Table 1.7: Changes on Adult labour force and Household characteristics

	Women			Men			Household	
	Age	Literate	Years of Education	Age	Literate	Years of Education	Household size	Number of Children
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price	-0.0917	-0.000327	0.00221	0.401	-0.0117	0.0258	-0.141	-0.133
	(0.0760)	(0.00301)	(0.0272)	(0.324)	(0.00940)	(0.240)	(0.103)	(0.0803)
Price× ASM Area	0.0973	0.0780	0.172	-3.346	0.0903	0.213	-0.284	-0.146
	(0.177)	(0.0199)	(0.184)	(0.926)	(0.0432)	(0.305)	(0.254)	(0.167)
Price× LSM Area	-0.893	0.00468	0.0577	-2.552	-0.0600	0.0887	-0.849	-0.633
	(0.418)	(0.0122)	(0.128)	(1.040)	(0.0600)	(0.527)	(0.477)	(0.370)
ASM Area	-0.721	-0.482***	-1.078	23.59***	-0.596*	-1.666	2.218	1.211
	(1.315)	(0.112)	(1.049)	(6.069)	(0.247)	(2.270)	(1.617)	(1.056)
LSM Area	5.121	-0.0643	-0.923	17.29*	0.287	-1.186	5.955	4.512
	(2.883)	(0.0808)	(0.807)	(7.360)	(0.392)	(3.634)	(3.198)	(2.583)
	8492	10296	7462	8195	10296	4580	10296	10296
R^2	0.005	0.008	0.028	0.022	0.035	0.037	0.040	0.026

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include district and year fixed effects, and individuals and households' controls, which include: individual's age and gender, household head's age and gender, literacy, asset, size, access to water and electricity; as well as an indicator of the household area.

1.8 Robustness checks

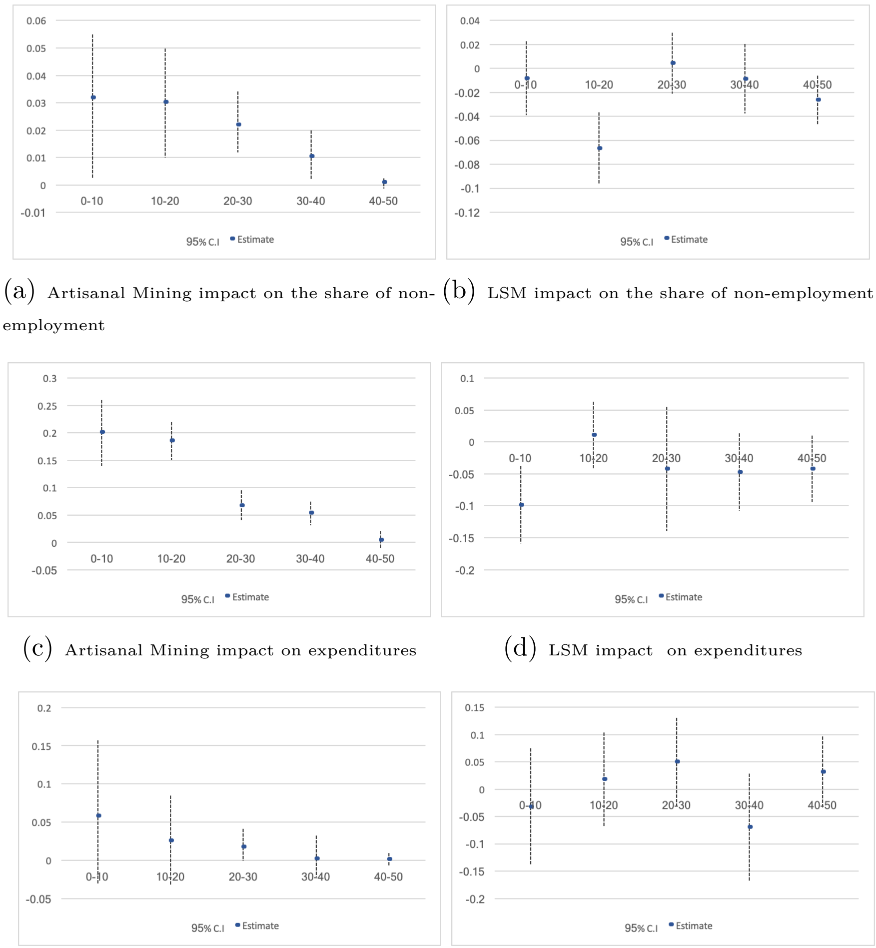
1.8.1 Distance buffer

The baseline results are confirmed when using alternative vicinity definitions. Table 1.8 replicates the reduced form estimates with buffers ranging from 10 to 50 km. The economic activity and domestic chores participation are significant with all buffers. Regarding educational outcomes, schooling attainment is significant and negative from 10 to 40 km and fails to reject the null with 50 km buffers. School lag is significant with all buffers. In Figure 1.5(a), I show that the positive impact of artisanal mine on the non-employment share remains significant up to 50 kilometres away from the artisanal mines. The figure shows the coefficient estimates of the impact of a one percent variation of the gold price on the share of non-employment of households located near an artisanal and small-scale mine, according to the distance between the household and the mine. The impact decreases with the distance and the results tend to suggest that the footprint of each artisanal mine extends up to 50 kilometres as the coefficient remains positive and significant up to this distance buffer. Figure 1.8 displays the estimated coefficients for different distance intervals of living near an LSM site. As we can see, the coefficient is never significantly different from zero.

Table 1.8: Effect of Artisanal Gold Boom on Children outcome: Buffer Sensibility

	Distance Buffer				
	(10km)	(20km)	(30km)	(40km)	(50km)
	(1)	(2)	(3)	(4)	(5)
Dep. variable : Price × ASM Area					
Economic Participation	0.0587*	0.130***	0.117***	0.107***	0.108***
	(0.0253)	(0.0163)	(0.0149)	(0.0227)	(0.0227)
Domestic Chores	0.0278*	0.130***	0.125***	0.116***	0.107***
	(0.0211)	(0.0166)	(0.0188)	(0.0207)	(0 .0231)
Not attending	-0.0278	-0.00297	-0.00066	0.0016	0.0045
	(0.0274)	(0.0080)	(0.0079)	(0.0081)	(0.0086)
School Attainment	-0.0287**	-0.0539***	-0.0475***	-0.0433***	-0.0399***
	(0.0106)	(0.0074)	(0.0082)	(0.0090)	(0.0102)
School Lag	0.0379***	0.0239***	0.0209***	0.0144*	0.0130
	(0.0088)	(0.0052)	(0.0059)	(0.0071)	(0.0076)

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include district and year fixed effects, and individuals and households' controls, which include: individual's age and gender, household head's age and gender, literacy, asset, size, access to water and electricity; as well as an indicator of the household area.



(a) Artisanal Mining impact on the share of non-employment

(b) LSM impact on the share of non-employment

(c) Artisanal Mining impact on expenditures

(d) LSM impact on expenditures

(e) Artisanal Mining impact on the head employment

(f) LSM impact on the head employment

Figure 1.5: Mining impact by distance to the mines

1.8.2 An alternative measure: Mining Deforestation

In the spirit of Mejía (2020), I use deforestation in the vicinity of gold mines as an alternative measure of gold mining intensity[9].

Table 1.9 presents the results of the interaction between international gold prices and mining deforestation. In terms of labour, only the effect on

[9] I obtain annual deforestation data from Hansen et al. (2013), which examines global Landsat data at a 30-meter spatial resolution to characterise forest extent, loss, and gain from 2000 to 2016. Gold mining is one of the main causes of deforestation in Mali (Thomas and Samassekou, 2003), as it affects forests through vegetation removal from mining areas, settlements, and roads. Deforestation in mining areas is thus a good proxy for mining activity and also has the advantage to capture both legal and illegal mining (Mejía (2020), Günther (2018), Andersson et al. (2015)).

children's economic participation remains positive and statistically significant, yet smaller than in the main results. Using this alternative measure, I find no evidence of a mining impact on school attendance, however column (4) shows a small effect on the child's performance at school. The probability that the child has attained the school grade given her age and a normal progression falls with the measure of mining intensity. This tends to suggest that the increased gold price increases the opportunity costs of children's time and thus increases the demand for child labour (substitution effect). In line with prior results I find no effect of LSM on children.

Table 1.9: Gold Boom effect on Children: Mining Intensity estimates

	(1) Economic Work	(2) Domestic Chores	(3) Not attending	(4) School Attainment	(5) School Lag
Price $\times$ Mining Deforestation	0.0214*	0.0103	0.003	-0.00027*	-0.0004
	(0.032)	(0.023)	(0.015)	(0.037)	(0.031)
N	10101	10101	10101	10095	10101
R^2	0.28	0.09	0.24	0.465	0.212

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each coefficient corresponds to a separate instrumental variable regression, controlling for district and year fixed effects, and individuals and households' controls, which include: individual's age and gender, household head's age and gender, literacy, asset, size, access to water and electricity; as well as an indicator of the household area. The independent variable the interaction between prices of gold and mining deforestation in the 10 km vicinity of gold mines.

1.8.3 Pre-trend Shocks

In this section, I take advantage of the 1995 DHS which is data available before the boom in gold prices in 2002. While, this year's survey does not collect data on child labour it includes information on children's school attendance. I make use of this information and check for pre-existing trends in schooling outcomes. To do that I replace the gold measure in equation (1.1) with an interaction between the initial gold measures in 2001 and time dummies. The results are presented in Table 1.10. The interaction between the gold variable and the survey year 1995 is insignificant for all regressions. This tend to suggest that there are no pre-tend shocks for household in the vicinity of mines relative to households further away, and this is true for all of the schooling outcomes.

Table 1.10: Robustness checks: Pre-trends

	(1) Not Attending OLS	(2) School Attain. OLS	(3) School Lag OLS
ASM Area ×1995	0.0312	-0.0756	0.0115
	(0.098)	(0.113)	(0.0341)
Indus. Area ×1995	0.190	0.155	0.562
	(0.0794)	(0.0550)	(0.139)
ASM Area ×2012	0.0518***	-0.0355***	-0.0130
	(0.140)	(0.127)	(0.0621)
Indus. Area ×2012	-0.0238	-0.0225	0.0253
	(0.0946)	(0.0628)	(0.0512)
1995	-0.173	-0.116	-0.752
	(0.0374)	(0.0306)	(0.0262)
2012	-0.198***	-0.0339	0.0141
	(0.0342)	(0.0247)	(0.0162)
N	10101	10101	10095
R^2	0.154	0.086	0.247

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include district and year fixed effects, and individuals and households' controls, which include: individual's age and gender, household head's age and gender, literacy, asset, size, access to water and electricity; as well as an indicator of the household area.

1.9 Conclusion

Gold mining plays an important role in some developing countries as it is a large source of income for governments and households. However, to date there is mixed evidence on the overall impact of mining on local populations. I contribute to this literature by estimating the local impact of increasing international gold prices on child labour and schooling, in a context where both large-scale and artisanal and small scale mining coexist. Particularly, I estimate the effect on children's economic, domestic participation and school attendance and attainment using a difference-in-differences approach. I use geographic information systems (GIS) to estimate the location of legal artisanal and large-scale gold mines and define a local measure of exposure to the gold boom, as the interaction between mining areas and international gold prices. I then combine this information to household and child labour data, from the Demographic and Health Survey (DHS). I find that the gold price expansion rises the probability that children work. This is quantifiable as a one percent increase in the price of gold increases child economic participation by 0.06%. Similarly, the probability of performing domestic chores increases by 0.03% for every one percent increase in the gold price. I find no evidence of a mining impact on school attendance, however, the probability that the child has attained the school grade given her age and a normal progression falls during the gold boom in proximity to artisanal mines. A one percent increase in the gold price reduces school attainment by 0.0287% in areas which are within 10km to listed artisanal mines.

Furthermore, I investigate potential mechanisms through which gold mining could affect children outcomes and assess to what extent they can explain the baseline findings. While the results are not driven by under-investment in schools nor endogenous migration, they capture an actual substitution effect. The results show that the measure of mining activity is associated with increased economic activity at the survey level, within 10km of an ASM site. A one percent increase in the price of gold decreases non-employment by 0.008% in the vicinity of artisanal mines. Nevertheless, one limitation of this study is that, I am unable to observe impacts on the intensive margin of schooling. The reason is that there is no detailed data available on educational histories for Mali. One avenue for future research in this area would be to address such data limitations. Collecting survey data on how parents allocate the time children spend in all activities, i.e. schooling and labour may lead to further important insights.

Chapter 2

The Impact of Precipitation Shocks on Allocation of Time in Rural Ethiopia

2.1 Introduction

Rural households in Ethiopia rely heavily on agriculture as their primary source of income. This implies that households' agricultural production and revenue are vulnerable to considerable variability given that crop production is rain-fed (Ademe et al., 2019). Moreover, only a few have access to irrigation and insurance and credit markets are weakly developed. Therefore, households have fewer options to cope with shocks, and as a result, this creates a potential effect on poverty and hence household welfare. Given that a growing body of evidence predicts climate change to increase the variability, intensity and uncertainty of precipitation shocks[1], understanding how households respond to precipitation shocks has become an important issue.

Jacoby and Skoufias (1998) show that in developing countries, consumption fluctuations are smaller than income fluctuations. They show that households can, to some extent, protect themselves against observed variation in incomes. The literature documents two main mechanisms through which this

[1] See for instance: Hulme et al. (2001); Desanker and Magadza (2001); Hulme et al. (2005).

occurs. There are ex-ante risk coping strategies, whereby households use income smoothing strategies in order to protect themselves against possible future income shock. This is often accomplished by choosing conservative production, crop diversification or engaging in precautionary savings (Kochar, 1999; Ito and Kurosaki, 2009; Rose, 2001). Post shock behavioural responses tend to mitigate impacts of the shock. These include borrowing from formal and informal sources (Wickramasinghe and Fernando, 2017), drawing down accumulated savings, and adjusting labour supply (Rose, 2001; Trinh et al., 2020).

I use survey data from Ethiopia to examine the effect of precipitation shocks on the participation in labour activities, by gender and activity. Precisely, I study how adult males and females allocate their time between various labour activities when confronted by positive or negative precipitation shocks. These activities include agricultural activities, non-agricultural work (self-employment or not), casual public works, (salaried) wage work, unpaid traineeships and household chores. I merge individual-level data on time allocation to different labour activities, with re-analysis precipitation data. This allows me to observe and measure the effects of agricultural productivity shocks on the time allocation into various activities.

Additionally, I take advantage of the heterogeneity of the impact of precipitation on agriculture to examine and understand the channels through which precipitation shocks impact time allocation decisions. To do this, I implement the strategy in Maitra and Tagat (2019a) and make use of the large scale irrigation investment that started in the 1970s as part of the government-owned state farms. This project mainly consisted of the construction of dams and reservoirs (Awulachew, 2019). Strobl and Strobl (2011) and Blanc and Strobl (2014) find that dams do not help agricultural production in upstream districts, leaving farmers and households in upstream areas of rain-fed districts more vulnerable to adverse effects arising from precipitation variation. I argue that the impact of precipitation shocks should hence differ by whether the district is rain-fed or has an irrigation system in place. I show that households and farmers in the dam-fed districts, should benefit from a more stable agricultural production and hence less volatile incomes.

I find that both women and men use different time allocation of labour strategies in response to exogenous precipitation shocks. The results also indicate the importance of the Public Works[2] (PW) programme, in rural Ethiopia. Rural households use PW as insurance against agricultural (productivity) shocks. A precipitation shock in February, which corresponds to the beginning of the Belg season and the planting stage for major crops and cereals, is associated with approximately a 20 percentage point increase in the time devoted to casual public works by men and women. The results show a declining time allocation to attending education institutions (unpaid traineeships) by men and women in response to precipitation shocks. This possibly affects their chances for human capital accumulation, which in turn, could have potential negative long-run consequences for their welfare. Because variations in labour allocations in response to precipitation shocks are usually short-run responses, there could be long-run implications of not attending education institutions.

Furthermore, I find that precipitation shortages result in females increasing their time allocation to casual public works. Males in contrast, respond to negative precipitation shocks by increasing their time in regular wage/salary work. The evidence shows that in districts with irrigation, the are no effects of extreme weather shocks on the time allocated to the different labour activities for both gender, suggesting that precipitation shocks are more prone to cause variations in rain-fed districts.

The interest in how agricultural productivity shocks, measured by precip-

[2]The Public Works (PW) programme in Ethiopia provides food, cash or a mixture of both, in return for work. It is mostly dominated by the Productive Safety Net Program (PSNP) which acts as a programme of employer-of-last-resort in rural Ethiopia (Hirvonen and Hoddinott, 2020). PSNP operates across widespread geographies and rural communities to provide payments to households that can contribute to build infrastructure and public goods. The programme's goal is to assure food consumption, and simultaneously to protect and develop assets along with services, to households that are both chronically food insecure and poor and often affected by shocks.

itation shocks impact households in Ethiopia, has grown in recent years. Evan and Pankhurst (1994) noted that women's activities are a prevalent coping mechanism for poor households, in response to precipitation shocks. These activities included making local products, collecting firewood and dung or handicrafts. Woldenhanna and Oskam (2001) provide some regional evidence that in Tigray region (northern Ethiopia), households diversify into non-farm activities. Especially, wealthier families may enter higher return activities, whereas poorer household members seek wage labour. Porter (2012) finds evidence that households are diverting their efforts towards relatively higher return activities with the intention to smooth income and consumption in the face of shocks. Using village-level panel, Colmer (2013) estimates the impacts of climate variability on time spent in child labour activities as well as participation in education and labour activities. He finds that increased climate variability is associated with increases in the time spent on farming activities and decreases in the number of hours spent on domestic chores.

The contribution of this Chapter is three-fold. First, although several studies provide evidence on the effect of precipitation shocks on household labour time allocation, studies that examine monthly variations in precipitation during the growing season are still nascent. Considering monthly variations in precipitation shocks enables me to analyse if and how a specific month of the growing season is essential in contributing to household wellbeing. Knowledge and evidence on the exact timing of the adjustments in time allocation are imperative for effective policy-making to help households insure against such shocks. This chapter's second contribution lies in providing a deeper understanding of how gender differences in the allocation of time come about in rural Ethiopia, giving more insight into intra-household responses to weather shocks. Third, I present evidence on the importance of major infrastructure projects, such as irrigation dams, in protecting against weather shocks, ex-ante.

The rest of the Chapter is as follows. Section 2.2 is devoted to the data and provides a summary of the main variables used in the analysis. Section 2.3 outlines the empirical strategy used to examine the effect of positive and negative precipitation shocks on the allocation of labour in different household activities. Section 2.4 presents the results and section 2.5 investigates heterogeneous impacts of precipitation shocks and the implication of irrigation systems. Lastly, Section 2.6 closes with a discussion on policy recommendation and a conclusion.

2.2 Data

I use data from multiple sources for the analysis. These include (i) data from two rounds of the employment schedule of Ethiopia Socioeconomic Survey (ESS), (ii) the agricultural module of the ESS, which provides information on crop production at the woreda (district) level, (iii) monthly historical precipitation at the district level from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), (iv) data on water resources and irrigation development in Ethiopia from Awlachew et al. (2007) and, (v) the Geo-referenced Database on Dams from the Food and Agriculture Organization (FAO).

2.2.1 Ethiopia Socioeconomic Survey (ESS)

I obtain data on time use in various labour activities from the Ethiopia Socioeconomic Survey (ESS). The ESS is a joint project between the Central Statistics Agency of Ethiopia (CSA) and the World Bank Living Standards Measurement Study-Integrated Surveys. The ESS collects household and panel data in rural and urban areas on a variety of household and community level characteristics also related to agricultural activities. While the first wave implemented in 2011-12 covered only rural and small-town areas, the second wave in 2013-14 added individuals from large town areas. The existing panel data (2011/12-2013/14) is only for rural and small towns.

The ESS collects data on labour, and more importantly, it provides data on time allocation to different activities at the individual level. The survey provides data on household members time use for a reference week. For each of the past seven days, defined as the reference week, household members report the number of hours spent in various labour activities. These activities comprise agricultural activities, non-agricultural work (self-employment or not), casual public works, (salaried) wage work and unpaid traineeship and any other work. I aggregate over activities, over the past seven days, to get a measure of time allocation and use the reference week's date to match time allocation to different activities to precipitation (productivity) shocks by month.

The data also include a multitude of household and individual characteristics. More precisely, the age, gender, literacy, religion, rural/urban residence, household size and monthly per capita household expenditure. It also includes livestock ownership which refers to the number of livestock units. In Ethiopian pastoral communities, livestock ownership serves a good proxy for wealth. Oxen ownership, household size and the number of dependent individual per household serve as indicators of draught animal and human labour availability, respectively. I restrict the analysis to men and women of working age (aged 15-65) and living in rural areas of Ethiopia. The two rounds of the survey took place from September to April.[3] Figure 2.1 shows that for the two rounds, there is enough variation in the number of households surveyed in each month. The data contains information on the woreda[4] (district) of residence.

I use this data on time-use to calculate the total number of hours each individual allocated to different labour activities during the past week. I first classify these into three groups: total hours worked (which is the sum of household agricultural activities), non-agricultural work (self-employment or not), casual public works, (salaried) wage work and unpaid traineeships and any other work; domestic chores (hours worked in attending domestic chores); and total hours attending educational institutions. Table 2.1 presents the average of the number of hours spent in the different activities in the reference week, for both genders. The descriptive statistics in Table 2.1 show consider-

[3] The data collection covers the belg crop season, which receives rainfall from February to April.

[4] It is the third recognized administrative division of Ethiopia, a district-level government.

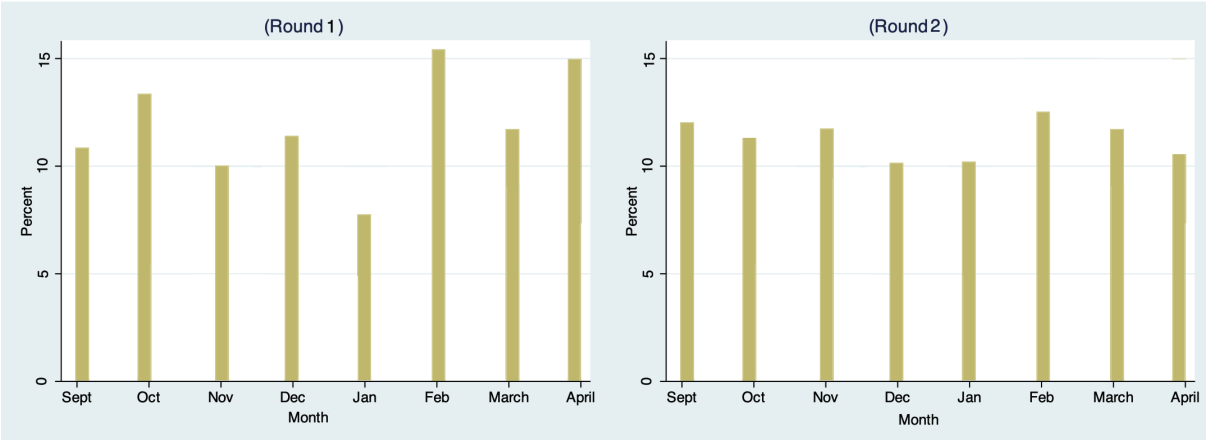


Figure 2.1: Percentage of Households Surveyed per months and per rounds

Table 2.1: Descriptive Statistics: Average Number of hours in Different Activities

	Female		Male		
	Mean	SD	Mean	SD	DIFF
Total Hours	29.53	2.61	40.30	2.39	-10.77***
Household chores	1.49	0.27	0.43	0.09	1.06***
Unpaid traineeship	4.21	3.82	7.94	4.52	-3.73***
Agriculture work	10.56	5.38	16.63	4.90	-6.07***
Non agriculture work	10.03	3.75	4.63	2.52	5.42***
Casual Public work	1.56	0.66	3.32	0.81	-1.76***
Work for wage/salary	1.65	1.71	7.34	1.62	-5.69***
Sample	8028		11888		

Notes:Authors' calculations using ESS data, round 1 and 2. Total hours worked excludes collecting water, wood and childcare. Significance of difference by gender computed using a t-test. Significance * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

able gender differences in allocating time to different labour activities. Male adults spend on average approximately 11 hours total hours (40.30 vs 29.53), they spend more time in agriculture (16.63 vs 10.56) as well as in work for wage/salary (7.34 vs 1.65) and in unpaid traineeships (7.94 vs 4.21). In contrast, female adults spend more doing household chores (1.49 vs 0.43) and doing non-agricultural work (10.03 vs 4.63).

The data also show differences in allocating time to the different labour activities over the different survey months. Figure 2.2 displays the mean number of hours worked by adult males and females in different labour activities by month, for the period of the survey. Regardless of the month of the survey, male adults allocate more time in agricultural, wage/salary, casual/public works and unpaid traineeship. In comparison, women spend more time on household chores and other non-agricultural work. Both males and females allocate more time to agricultural work during the months of September to December. Conversely, in these months they spend less time in unpaid traineeships. The time allocation in wage/salary work and casual public works is relatively stable through the year, with a decrease in December for wage/salary work and a peak in February for casual pubic works.

In Table 2.2 I show the averages and standard deviations of the main set of individual and household characteristics for the full sample (columns 1 and 2) and separately for men (columns 3 and 4) and women (columns 5 and 6). The mean age of the individuals in the sample is 28.76 years, with females being a little older (32.69 years old). 44.86% of the sample are Orthodox, more than 30% are Muslims, and around 20% are protestants. Around 36% of the households use fertilizers, while 16% have access to credit. 24% of households have both crops and livestock. The mean household size is 5.87, with an annual per capita consumption of ETB. 4115.98.[5] I use these individual and household characteristics as further controls in the regressions.

2.2.2 Precipitation Data and the Definition of Precipitation Shocks

The study makes use of monthly precipitation data from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). Spanning 50° S-50° N (and all longitudes), this re-analysis precipitation dataset, was collected from 1981 to near-present and incorporates 0.05° resolution satellite imagery with on-site station data to generate a gridded precipitation time series for trend analysis.[6] The advantage of satellite-based data is better spatial coverage

[5] As of April 2021, the current exchange rate of EUR to Ethiopian Birr is 1 EUR = 49.2944 ETB.

[6] According to the European Centre for Medium-range Weather Forecasts (ECMWF), *"Reanalysis data provide the most complete picture currently possible of past weather and climate. They are a blend of observations with past short-range weather forecasts rerun with modern weather forecasting models. They are globally complete and consistent in time and*

Table 2.2

	All		Male		Female	
	Mean	SD	Mean	SD	Mean	SD
Age	28.76	13.94	26.10	13.80	32.69	13.18
Can read and write(%)	54.17	0.50	69.20	0.46	32.72	0.47
Household size	5.87	2.38	6.01	2.29	5.73	2.46
Per capita Consumption	4115.98	4641.20	4127.49	4806.47	4104.85	4476.25
Religion						
Orthodox(%)	44.86	0.50	47.91	0.50	40.62	0.49
Protestant(%)	20.77	0.41	19.35	0.40	22.73	0.42
Muslim(%)	31.62	0.47	30.15	0.46	33.66	0.47
Farm type						
Crop(%)	3.40	0.18	2.68	0.16	3.90	0.19
Livestock(%)	2.68	0.16	2.55	0.16	2.77	0.16
Both(%)	24.27	0.43	11.92	0.32	32.60	0.47
Fertilizer(%)	36.17	0.37	30.27	0.46	44.97	0.50
Access to credit (%)	16.38	0.48	13.75	0.34	20.28	0.40

of weather data compared with weather stations, especially for developing countries such as Ethiopia where sometimes few weather stations operate. A specific strength of this dataset compared to existing precipitation databases is its high resolution, since the 0.05° resolution is a unique threshold (Katsanos et al., 2016).

In order to match precipitation to the woreda in which a household lives, I use the closest point on the grid to the centre of the woreda. I then assign each level of precipitation to the woreda in the given month and year. This method allows me to match precipitation data to 235 woredas across the country for 33 years. All households living in a woreda are assigned the woreda level precipitation. One could argue that aggregating precipitation this way implies that shocks in any one part of the woreda affect outcomes in a different part of the same woreda. However, the woreda is the smallest administrative unit in Ethiopia, for which I can carry out this analysis[7].

are sometimes referred to as 'maps without gaps'"

[7] I also check for serial correlation of precipitation: if negative shocks a particular year are correlated with negative shocks the following year, it becomes tricky to determine the

Figure 2.3 shows considerable variations in median precipitation for the period 1981-2014, over the months. When I combine all woredas, the highest monthly median precipitation is more than 500 mm in July and approximately 50 mm in December. The line inside of the rectangle in Figure 2.3 represents the median, and the rectangle itself represents the interquartile (75th-25th) range.

I calculate the precipitation shock for each woreda and each month in the following way. First, I compute the mean (μ_{km}) and the standard deviation (σ_{km}) in precipitation for each woreda (k) and each month (m) over the 30 years before the date of the survey. I then compute a standardized measure of precipitation $z_{kmy} = (R_{kmy} - \mu_{km})/\sigma_{km}$ [8], where R_{kmy} is the precipitation in woreda k in month m in year y. Mirroring McKee et al. (1993), I define woreda k in month m in year y to experience a precipitation shock if $z_{kmy} < -1$ or $z_{kmy} > 1$. The precipitation shock is considered a positive shock if $z_{kmy} > 1$ and a negative shock if $z_{kmy} < -1$. These precipitation shocks are not to be taken in an absolute sense, as I do not compare woredas that are prone to higher average precipitation versus those that are prone to lower average precipitation. They are high or low-precipitation for each woreda for each month, relative to the historical average for that woreda in that month.

Figure 2.4 shows the percentage of woredas in each month and for each survey round that experience a negative precipitation shock or positive precipitation shock. Figure 2.4 also shows, that in any given month, up to 80% of woredas might be affected by positive or negative shocks. Figure 2.5 present the histograms of the distribution of deviations (z) from mean historical precipitation in the sample, by year. There are more negative shocks than positive. Negative shocks are of a much greater magnitude in the second round, confirming the worrying trend of climate change predictions.

extent to which the analysis is picking up the impacts of a single shock or several years of precipitation shocks. I find no significant evidence of serial correlation across years.

[8] This standardized measure of precipitation deviation is widely used in the literature and is recognized to be the best method of calculating regional averages for precipitation as it allows weighting the standardized anomalies (Jones and Hulme, 1996).

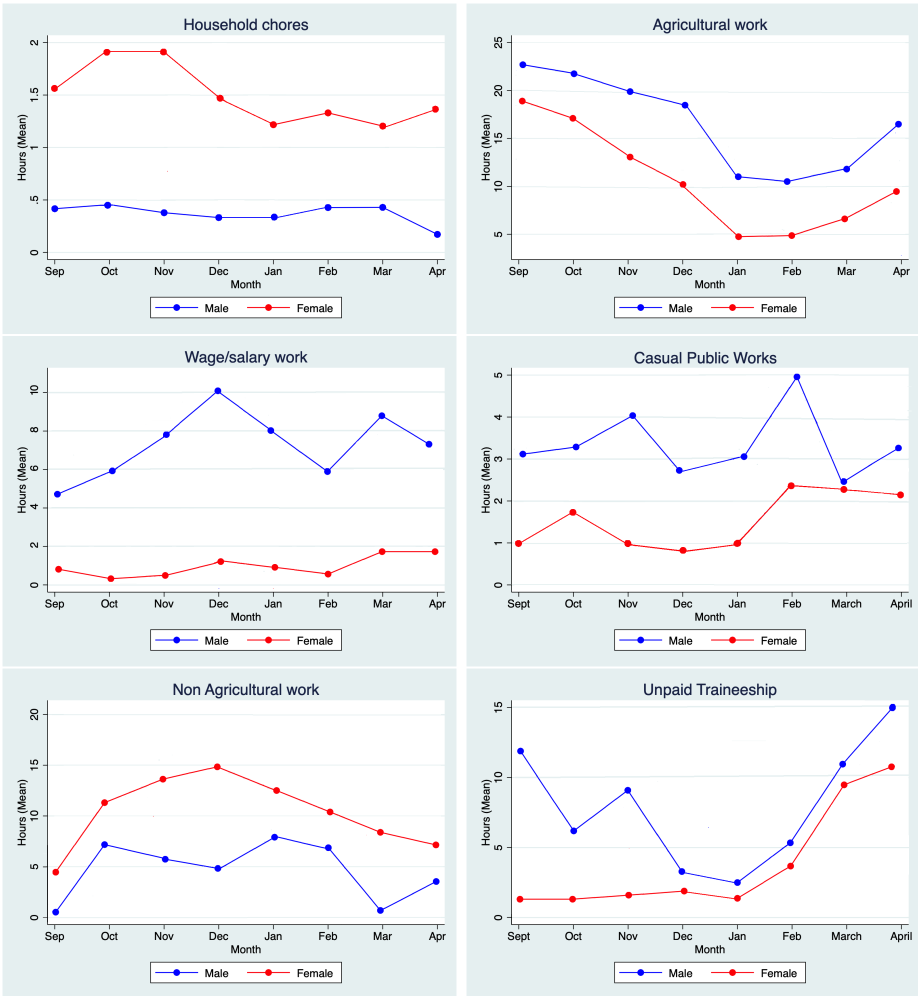


Figure 2.2: Mean Number of Hours in Different Activities by Survey Month

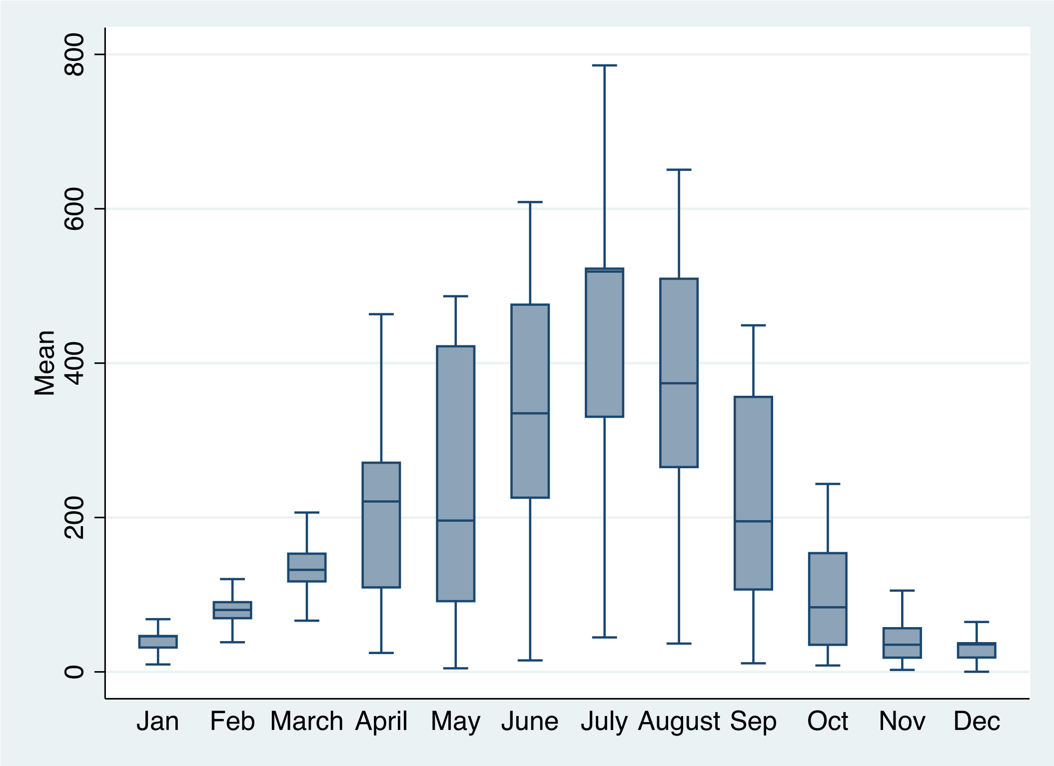


Figure 2.3: Median and Interquartile Range of Precipitation 1981-2014, by month

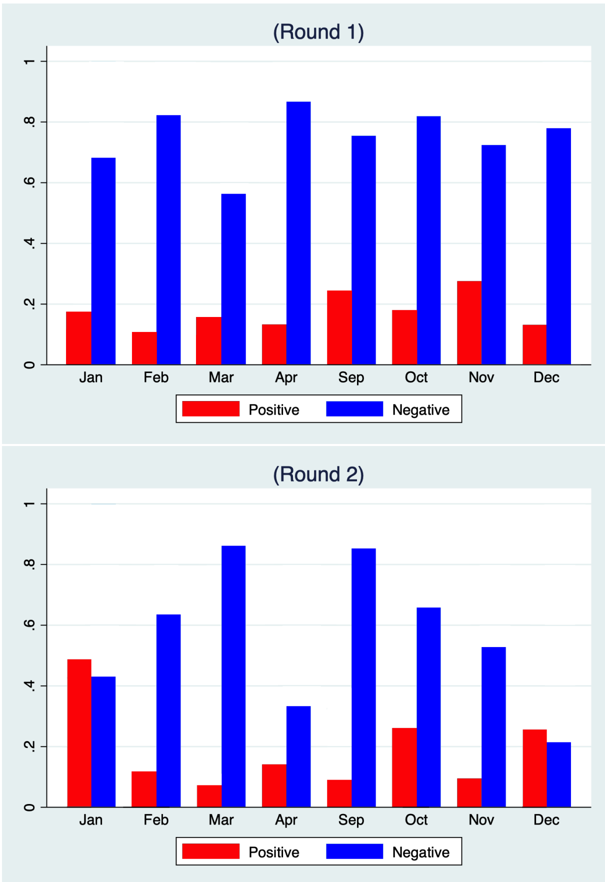


Figure 2.4: Proportion of woredas (districts) with Positive and Negative Precipitation Shock by Month and Survey Round

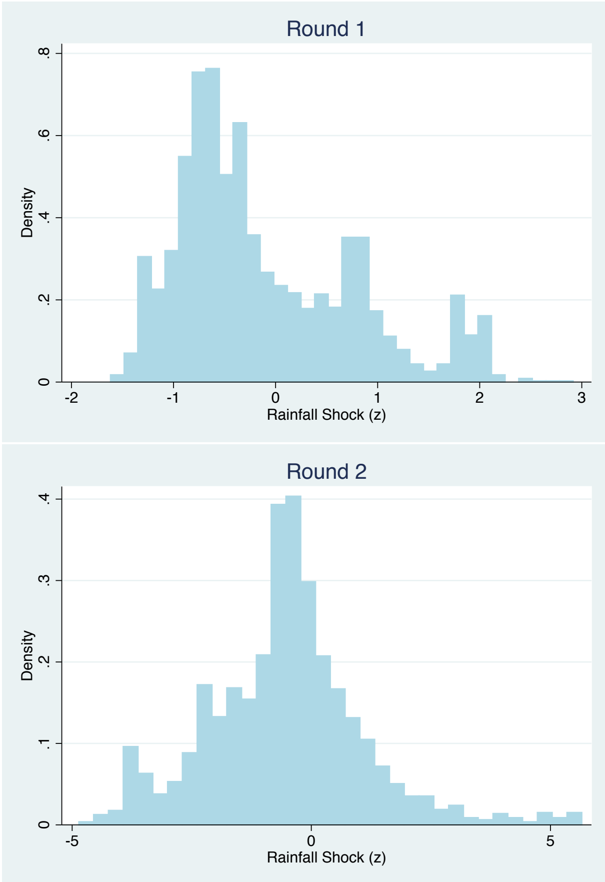


Figure 2.5: Distribution of deviations from average historical precipitation by Survey Year

2.2.3 Precipitation Shocks and Agricultural Productivity

Agriculture is the source of livelihood to a vast number of Ethiopian rural households. It is also the basis of the national economy, with small-scale subsistence farming being predominant. This sector employs more than 80% of the labour force and accounts for 45% of the GDP and 85% of export revenue (Di Falco et al., 2012). Ethiopian agriculture depends heavily on natural precipitation, with irrigation agriculture accounting for only 5% of the country's total cultivated land (Asrat and Anteneh, 2019). Hence, the amount and temporal distribution of precipitation during the crop season are critical to crop yields and can explain differences in agricultural productivity in Ethiopia.

To examine this relationship, I construct a panel covering monthly crop production data from 167 Ethiopian woredas over the periods 2011-2014. This panel uses a subset of the 235 districts for which I have monthly precipitation data. The data on crop production comes from the agricultural module of ESS. I use data on total production (quantity in kilos) and area (in thousands of hectares)[9] under cultivation for maize and sorghum, the two main crops produced in Ethiopia.

$$y_{kt} = \beta_0 + \beta_1 \xi_{kt} + \theta_k + \mu_t + \epsilon_{kt} \tag{2.1}$$

y_{kt} denotes the outcome of interest in woreda k in year t. I start by observing the impact of precipitation shock in woreda k in year t (ξ_{kt}) on area cultivated and on the total production of maize and sorghum. I reiterate the analysis outlined in Section 2.2.2 at the year level such that $\xi kt = 1$ if woreda k faced any precipitation shock in year t.

β_1 shows the impact of the precipitation shock ξ_{kt} in woreda k in year t. I also add controls for woreda θ_k and year fixed effects μ_t. The woreda fixed effects control for time-invariant characteristics (for example soil types and socio-economic characteristics that vary across woredas) and the year fixed effects allow me to examine whether the relationships change over time. Table 2.3 displays the results.

In columns 1 and 2, I find that a precipitation shock significantly increases the area cultivated and total production of both maize and sorghum. I also separate precipitation shocks into positive and negative precipitation shocks and estimate the following equation:

$$y_{kt} = \beta 0 + \beta 1 \xi^{+}_{kt} + \beta 2 \xi^{-}_{kt} + \theta_k + \mu_t + \epsilon_{kt} \tag{2.2}$$

where ξ^{+}_{kt} and ξ^{-}_{kt} are binary variables equal to 1 if woreda k in year t faced a positive precipitation shock (i.e. flood) and experienced a negative precipitation shock (i.e. drought) respectively. This enables me to isolate both effect

[9] Some observations are expressed in “Timad”, I use the FAO standard conversion for the “Timad”, treating them as 1/4 of an acre, which is about 0.405 hectare.

of positive and negative precipitation shocks.

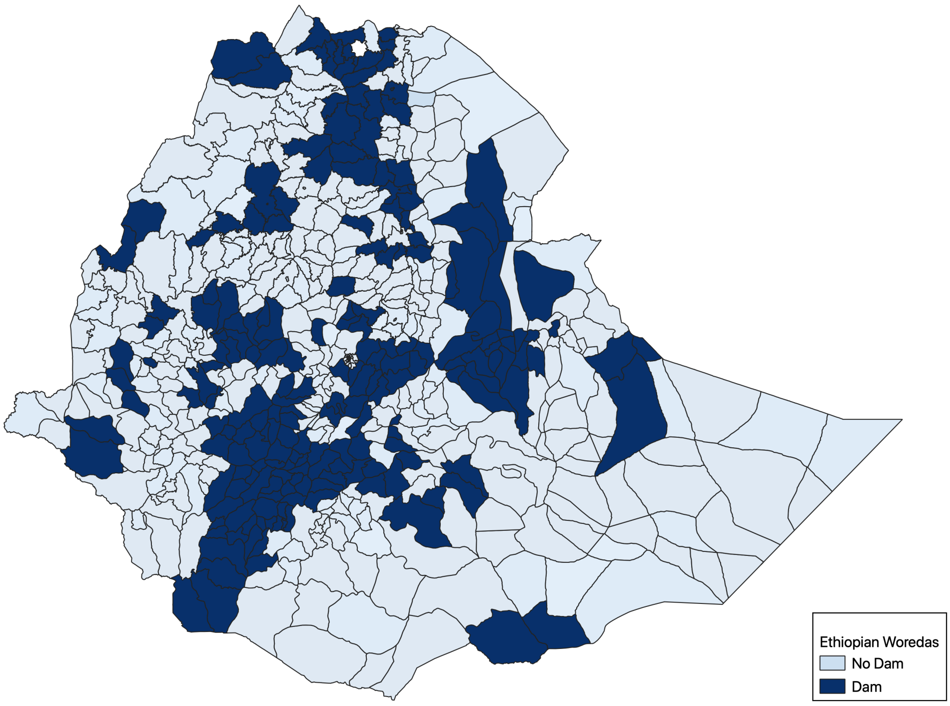
The results are displayed in columns 5-8 in Table 2.3. Positive and negative precipitation shocks affect area cultivated and production of both maize and sorghum differently. While a negative precipitation shock reduces the area cultivated and total production of maize and sorghum, a positive shock, has an increasing effect. These results show the importance of studying both positive and negative precipitation shocks as they have different effects on crop production.

2.2.4 Irrigation Systems in Ethiopia: Dams

To examine and understand the channels through which precipitation affects labour time allocation, I use the heterogeneous impact of precipitation on farming. To do this, I take advantage of the irrigation investment that Ethiopia started in the 1960s as part of the government-owned state farms. This project mainly consisted of the construction of dams and reservoirs (Awulachew, 2019). Often constructed as large artificial dams, with a wall across the river valley, the dams channel the collected water to downstream woredas, through a chain of irrigation canals. These woredas in which the dams are situated are classified as irrigation-fed woredas.

Dams make it possible to store water for later use and hence protect from precipitation shortages. Protecting against precipitation shortages is particularly important for regions where water varies considerably during the wet and dry seasons. Dams also allow keeping surplus runoff that would typically flow back to the ocean without being used. By enabling control over the flow of water in dam-fed areas, dams ensure agricultural production against variations arising from precipitation shocks. Households and farmers in the dam-fed areas should benefit from a more stable agricultural production and hence less volatile incomes. Typically, dams do not benefit agricultural production in upstream areas, leaving farmers and households in upstream areas of rain-fed areas more vulnerable to adverse effects arising from precipitation variations (Strobl and Strobl (2011); Blanc and Strobl (2014)). This suggests that time

Figure 2.6: Irrigation development in Ethiopia: Woredas with and without Irrigation



allocation responses to precipitation shocks should differ by whether the area is rain-fed or has an irrigation system in place.

To identify rain-fed or irrigation-fed areas, I use data on water resources and irrigation development in Ethiopia from Awlachew et al. (2007), the Georeferenced Database on Dams from the Food and Agriculture Organization (FAO) as well as the Global Georeferenced Database of Dams (GOODD) from Mulligan et al. (2020). This dataset I constructed provides valuable information on location, height, reservoir capacity, surface area, the primary purpose and the upstream catchment areas of dams. All this information makes it possible to identify the downstream (dam-fed) and upstream (rain-fed) woredas.

Figure 2.6 shows the woredas with (light blue) and without (dark blue) irrigation systems. There are two potential limitations to this data. First, classifying an entire woreda as being rain-fed or irrigation-fed is debatable. Even if an entire woreda is classified as irrigated, it is unclear whether the entire woreda benefits from irrigation. Unfortunately, the woreda is the lowest administrative level at which this study can be conducted. The second limitation results from the potential endogeneity in the placing of irrigation systems. Blanc and Strobl (2014) discuss that the construction of dams essentially depends on how wealthy local authorities are and that dam construction is as such correlated with the local authorities' wealth. Nevertheless, in this study, I am effectively studying differences in dam construction across woredas, and this should decrease the bias resulting from the correlation between state wealth and dam construction.

Nonetheless, different characteristics other than local authorities' wealth could influence the construction of irrigation systems. The geographical topology may play an essential role in determining the possibility of dam construction in a woreda. Blanc and Strobl (2014) and Duflo and Pande (2007) report that the river length, the elevation of the district, and the river's gradient are important determinants of the building of dams in a district. They show that river gradients between 1.5-3% or more than 6% favour the building of dams; however, gradients less than 1.5% or between 3-6% do not. In line with Blanc and Strobl (2014) and Duflo and Pande (2007), I predict the number of dams in a woreda using the geographical topology of the woreda and estimate the following first stage regression:

$$\hat{D}_{drt}=\alpha_1 + \textstyle\sum_{g=2}^{5} \alpha_{2g}(RG_{gd} \times \bar{D}_{rt}) + \sum_{g=2}^{4} \alpha_{3g}(E_{gd} \times \bar{D}_{rt}) + \sum_{g=2}^{5} \alpha_{4g}(G_{gd} \times \bar{D}_{rt}) + \alpha_5(X_d \times \bar{D}_{rt}) + \lambda_d + \mu_{rt} + \epsilon_{drt} \quad (2.3)$$

$\hat{D}_{drt}$ is the number of dams built in woreda d, region r and in year t. RG_{gd} represents the fraction of river area within a woreda d that has gradient level g; E_{gd} denotes the fraction of a woreda that has gradient level g. I divide the woredas into five gradient areas (less than 1.5%, 1.5-3%, 3-6%, 6-10% and over 10%) and four elevation groups (in meters) - 0-250, 250-500, 500-1000 and over

1000. X_d is a vector of controls including woreda area and river length, and district and region-year fixed effects. Lastly, $\bar{D}_{rt}$ is the number of dams built in region r until year t. This equation enables me to predict the number of dams $\hat{D}_{drt}$, and to create a binary variable "irrigated", which is equal to 1 if the downstream woreda contains at least one dam ($\hat{D}_{drt} > 0$). Woredas with "irrigated" equal to 0 are classified as rain-fed and I estimate the regression separately for the irrigated and rain-fed woredas.

2.3 Empirical Strategy

I use a two-period agricultural production model developed by Rose (2001).[10] In this model period 1 represents the planting stage, period 2 is the harvesting stage and households make labour decisions in both periods. This is illustrated in Figure 2.7. There is a random variable ξ (such as precipitation) that affects agricultural production and that is realised at the onset of period 2. In period 1, households know the average over time and the variability of the distribution of ξ but not its realisation. In period 2, households now know the realisation of ξ and can tailor their time allocation decisions accordingly. Depending on precipitation affects labour time allocation decisions in period 2 (when precipitations deviate from their long-run average), incomes are impacted. If households indeed use the labour market to protect against these shocks, one could expect to see an impact on time allocation to different labour activities.

Figure 2.7: Two-period Framework, Rose (2001).

To estimate the effect of a precipitation shock on the decision to engage in

[10] This model is also used in Silwal (2016) and Colmer (2013). While Rose (2001) looks at ex-ante and ex-post effects, I only consider ex-post labour time allocation decisions in this analysis.

the different labour activities for household members, I consider the following regression[11]:

$$S_{ihdmt} = \alpha_0 + \alpha_1 \xi_{dt} + \alpha_2 X_{ihdmt} + \theta_d + \mu_t + \rho_m + \epsilon_{ihdmt} \tag{2.4}$$

S_{ihkmt} represents the supply of labour of individual i, in household h, in woreda d, on month m and in year t. The measure of S_{ihdmt} includes the time allocated (in terms of number of hours of work) in the past seven days, by the individual in different labour activities (agricultural activities, non-agricultural work (self-employment or not), casual public works, (salaried) wage work and unpaid traineeship) and domestic chores. ξ_{dt} is defined in Section 2.2.3. α_1 shows the impact of occurring precipitation shocks on labour allocation decision. θ_d, ρ_m and μ_t represent a set of woredas, month and year fixed effects respectively. Last, I include, X_{ihdmt} a vector of individual and household characteristics (see Table 2.2) and ϵ_{ihdmt} is the disturbance term. The standard errors are clustered at the woreda level. To account for the difference between positive and negative productivity shocks (precipitation shocks), I further estimate a second specification which allows me to distinguish the effect of positive and negative shocks and examine whether these have symmetric impacts on time allocation to the different labour activities. The estimated equation is given by:

$$S_{ihdmt} = \alpha_0 + \alpha_1 \xi^{+}_{dt} + \alpha_2 \xi^{-}_{dt} + \alpha_3 X_{ihdmt} + \theta_d + \mu_t + \rho_m + \epsilon_{ihdmt} \tag{2.5}$$

The other variables remain unchanged.

[11] The strategy implemented mirrors that of Maitra and Tagat (2019a)

Table 2.3: Effect of Precipitation Shocks on Area Cultivated and Total Production of Maize and Sorghum

	Maize		Sorghum		Maize		Sorghum	
	Total Production	Cultivated Area	Total Production	Cultivated Area	Total Production	Cultivated Area	Total Production	Cultivated Area
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Precipitation Shock (ξ)	0.212***	0.00701***	0.416***	0.0093***				
	(3.625)	(0.833)	(22.87)	(6.592)				
Positive Shock (ξ^+)					1.476***	0.0521**	8.930***	0.0590**
					(16.30)	(3.710)	(144.8)	(42.45)
Negative Shock (ξ^-)					-1.933***	-0.0273***	-4.609***	-0.111***
					(16.18)	(3.456)	(195.0)	(57.16)
2012	0.0084**	0.0003	0.119	0.00273	-1.674*	-5.7514**	3.6113	-4.9914
	(4.645)	(1.039)	(27.07)	(7.619)	(4.642)	(1.038)	(26.27)	(7.369)
2013	0.0140	0.00048***	0.0470	0.0011*	0.0399	0.0015***	0.0859	0.00053
	(4.649)	(1.040)	(26.39)	(7.407)	(4.662)	(1.043)	(26.30)	(7.378)
2014	0.0318***	0.00081	0.0973	0.0023***	0.0415	0.0013***	0.107	0.00067
	(4.674)	(1.043)	(26.81)	(7.543)	(4.663)	(1.042)	(26.32)	(7.383)
Average in Normal Year	85.47	2.30	161.33	6.35	85.47	2.30	161.33	6.35
N	3836	4352	3364	3676	3836	4352	3364	3676
R^2	0.353	0.038	0.137	0.100	0.353	0.038	0.137	0.100

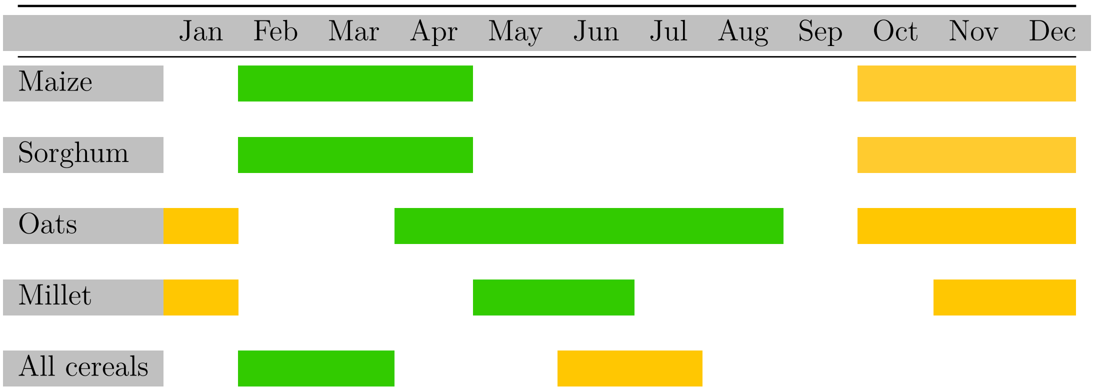
OLS regression results given by estimating equation (2.1) : Estimating equation is given by equation (2).

The regressions include year and district fixed effects. Area cultivated is in hectares and total production is in kilos.

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.4: Major Crop Calendar



The green areas represent the planting stage, harvesting stage is in yellow. Source: Food and Agriculture Organization (FAO) of the United Nation

Equations (2.4) and (2.5) account for occurring precipitation (productivity) shocks only. However taking into account the agricultural production, the households may tailor their time allocation in month m in response to precipitation shocks in preceding months. For example, consider the production of maize and sorghum (see Table 2.4). Planting of these crops is during the period Februray-April and harvesting is during the months October-December. Hence, a precipitation shock in June is as prone to impact output, as is a precipitation shock in September. To take into consideration this possible lagged effect, I extend equations (2.4) and (2.5) and estimate the following regressions:

$$S_{ihdmt} = \alpha_0 + \sum_{j=0}^{k} \alpha_{1j}\xi_{m-j,dt} + \alpha_2 X_{ihdmt} + \theta_d + \mu_t + \rho_m + \epsilon_{ihdmt} \tag{2.6}$$

and

$$S_{ihdmt} = \alpha_0 + \sum_{j=0}^{k} \alpha_{1j}\xi^{+}_{m-j,dt} + \sum_{j=0}^{k} \alpha_{2j}\xi^{-}_{m-j,dt} + \alpha_3 X_{ihdmt} + \theta_d + \mu_t + \rho_m + \epsilon_{ihdmt} \tag{2.7}$$

Here, k stands for the number of lags. Therefore in equation (2.6), α_{1j} shows the effect of precipitation shock j months preceding to the month of survey. When j=0 (month of the survey) equation (2.6) is the occurring effect of precipitation shocks measured in equation (2.4). Similarly, equation (2.7) is a broader version of equation (2.5). I estimate two variants of equation (2.6) and (2.7) for two lag durations: k=2 and k=4.

Another important source of variation relates to the exact timing of precipitation. shocksThis is essential as the cropping patterns, the amount of precipitation needed for each crop differ across the country, and precipitation shocks occur throughout several months (See Figure 2.3). Furthermore, evidence suggests that shocks early in the growing season can have a devastating impact as all the sown crops may suffer irreparable damage, resulting in significant economic losses for farmers. Indeed by the beginning of the Belg season, which follows the long dry season of Begl, the soil moisture is practically zero. Bewket (2009) shows that the event of adequate rainfall in the early periods of the Belg season is critical for main crops such as maize and sorghum production. Hence, precipitation shocks at different times of the growing season are likely to have different household incomes implications. As a result, households could react to precipitation shocks differently depending on which month the shock occurs. To account for this variation in precipitation shocks over months, I create interactions of the precipitation shock with the month of the survey (i.e. the month of the reference week) and estimate the following equation:

$$
\begin{aligned}
S_{ihdmt} = \alpha_0 + \sum_{m=1}^{8} \alpha_{1m}\gamma_m + \alpha_2\xi_{mdt} \\
+ \sum_{m=1}^{8} \alpha_{3m}(\xi_{mdt} * \gamma_m) + \lambda X_{ihdmt} \\
+ \theta_d + \mu_t + \rho_m + \epsilon_{ihdmtit} + \alpha_d + \epsilon_{idt} \quad (2.8)
\end{aligned}
$$

γ_m is a binary variable, equal to 1 if month = m and 0 otherwise. $\alpha_0 + \alpha_{1m}$ captures the time allocation in a normal month m, $\alpha_0 + \alpha_1 m + \alpha_2 + \alpha_{3m}$ gives time allocation in a month m that experiences a precipitation shock $\alpha_2 + \alpha_{3m}$

the change in time allocation in month m that experiences a shock relative to a normal month. I further examine the effects of positive and negative precipitation shocks by month, separately, and determine:

$$
\begin{aligned}
S_{ihdmt} = \alpha_0 + \sum_{m=1}^{8} \alpha_{1m}\gamma_m + \alpha_2 \xi^{+}_{mdt} \\
+ \sum_{m=1}^{8} \alpha_{3m}(\xi_{mdt} * \gamma_m) + \alpha_4 \xi^{-}_{mdt} + \lambda X_{ihdmt} \\
+ \theta_d + \mu_t + \rho_m + \epsilon_{ihdmt} \qquad (2.9)
\end{aligned}
$$

2.4 Results

2.4.1 Effect of Precipitation Shocks on Consumption

Since precipitation shocks can negatively affect agricultural productivity, if households are unable to insure against this risk in returns, they may see their consumption decrease. I use equation (2.4) to investigate this and assess the effect of precipitation shocks on household expenditure. However in this case, the dependent variable is monthly per capita expenditure y_{hdmt} of household h in woreda d, in month m in year t. I include household characteristics such as average age, average literacy, religion, dependency ratio and household size, as well as woreda (θ_d), month (ρ_m) and year (μ_t) fixed-effects. I conduct this analysis at the household level with the standard errors clustered at the same level. Table 2.5 presents the results.

Column (1) shows that there is a negative relationship between precipitation shocks and monthly per capita consumption expenditure. The magnitude of the decline in per capita household consumption is a low Birr.30, which represents 0.73% of the mean per capita household consumption for the estimating sample of households. However, this result is not statistically significant and also holds when I include lagged values of precipitation shocks to the estima-

Table 2.5: Impact of Precipitation Shocks on Household Monthly Per Capita Consumption

	Per capita Consumption			
	Precipitation Shock		Positive and Negative Shock	
	(1)	(2)	(3)	(4)
Precipitation Shock (ξ)	-30.46	-47.25		
	(15.92)	(35.83)		
Lag (2months)		-30.18		
		(41.84)		
Lag (4 months)		12.32		
		(33.60)		
Positive Shock (ξ^+)			13.78	17.28
			(43.85)	(87.92)
Negative Shock (ξ^-)			-61.69	-16.70
			(38.61)	(89.78)
Positive lag (2 months)				32.86
				(111.1)
Negative lag (2 months)				26.99
				(109.2)
Positive lag (4 months)				-43.67
				(86.03)
Negative lag (4 months)				-88.07
				(79.89)
Mean normal Precipitation (month) N	78502	78494	78502	78494
R^2	0.315	0.315	0.315	0.315

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

tion in column (2). This finding is similar to Lertamphainont and Sparrow (2016). Columns (3) and (4) present the effects of positive and negative precipitation shocks, respectively. Neither a positive nor a negative precipitation shock has a statistically significant impact on per capita household consumption. The fact that precipitation does not have any statistical significance is consistent with the ability of households to smooth their consumption in the event of shocks to income. One possible hypothesis is that households do this via adjustments to their labour supply. I test this in the next section.

2.4.2 Effect of Precipitation Shocks on Labour Allocation

Table 2.6 shows the regression results fusing equations (4) and (5), by gender. Panels A and B display the effect for female and male, respectively. The bottom row in each panel shows the average number of hours in the survey week allocated to the different labour activities. Females increase time allocation to casual public works by 2.9% (as a percentage of the number of hours worked in a "normal" month) but reduce time in unpaid traineeships. The women in the sample are aged 15-60, so essentially a precipitation shock reduces the amount of time in higher education, potentially harming human capital accumulation. Males respond to precipitation shocks by reducing the time allocation to household chores (collecting water and firewood), and by also significantly increasing their time allocation to casual public works. The effects are large, particularly for the time spent in casual public works. Relative to the average number of hours worked in the corresponding activity in a "normal" month, males decrease their time allocation to household chores by 1.7% and increase their time allocation to casual wage work by 1.2%.

An important question is to what extent do men and women respond differently to precipitation shocks. I find that, both men and women increase their time allocation to casual public works following a precipitation shock and the there is no evidence of any gender difference[12]. The results show

[12] To test this, I use the test developed by Paternoster et al. (1998) and used in Maitra

that attending educational institutions differ by gender (p-value = 0.023): the reduction in time allocated to unpaid traineeships in response to a precipitation shock is significantly greater for female than for male.

Do positive or negative precipitation shocks have differential impacts on households responses? Table 2.6 displays the effect of too much rain (ξ^{+}) or too little rain (ξ^{-}) on time allocation in different labour activities. Men and women react to a negative precipitation shock by decreasing their time allocation to unpaid traineeships and there is significant gender difference in the effect of such a shock on time allocation to unpaid traineeships. There is no statistically significant effect on time allocation to unpaid traineeships in response to a positive precipitation shock. Moreover, the results suggest that men (but not women) react to negative precipitation shocks by increasing their time in regular wage/salary work and the difference is statistically significant, p-value = 0.012. The effect is rather small at 2.5% of the average in a "normal" month. Furthermore panel B shows that any deviation from the average (i.e., both positive and negative) leads to a reduction in time allocated to unpaid traineeships for men. The gender difference is statistically significant for both types of shock (p-value of difference = 0.008).

and Tagat (2019b). Take regressions on two different subsamples (i.e. male and female). For the same explanatory variable (i.e. precipitation), β_1 and β_2 express the estimated coefficients from the two subsamples, let $SE(\beta_1)$ and $SE(\beta_2)$ be the standard errors. The z-test for the difference between the two coefficients of regression is given by the following value: $z = \frac{\beta_1 - \beta_2}{\sqrt{SE(\beta_1)^2 + SE(\beta_2)^2}}$

Table 2.6: Effect of Precipitation Shocks on Time Allocation to Labour Activities

	(1) Household chores	(2) Agricultural work	(3) Non Agriculture work	(4) Casual Public work	(5) Work for wage Salary	(6) Unpaid Traineeship
PANEL A: WOMEN						
Precipitation Shock$^{\top}$ (ξ)	-0.0234	-0.156	-0.0604	0.0163***	0.0244	-0.0254*
	(0.0180)	(0.136)	(0.116)	(0.0343)	(0.0417)	(0.0645)
Positive Shock$^{\perp}$ (ξ^{+})	-0.00681	0.165	0.214	0.0264	-0.0873	-0.233
	(0.0412)	(0.305)	(0.282)	(0.0793)	(0.0944)	(0.153)
Negative Shock$^{\perp}$ (ξ^{-})	-0.0136	-0.00355	0.00039	0.0162***	0.0419	-0.0836***
	(0.0378)	(0.258)	(0.221)	(0.0643)	(0.0738)	(0.132)
Average hours in Regular Month	1.33	9.48	11.35	0.56	0.52	1.95
N	38714	38654	38558	38858	38870	38870
PANEL B: MEN						
Precipitation Shock$^{\top}$ (ξ)	-0.00498*	0.0669	-0.0494*	0.00987**	0.0406	0.0553
	(0.00758)	(0.146)	(0.116)	(0.0518)	(0.0609)	(0.0721)
Positive Shock$^{\perp}$ (ξ^{+})	0.00729	-0.159	0.108	0.0145	-0.141	-0.476**
	(0.0176)	(0.340)	(0.270)	(0.124)	(0.144)	(0.168)
Negative Shock$^{\perp}$ (ξ^{-})	-0.0180	0.0239	0.0796	0.000506	0.0177**	-0.0655***
	(0.0161)	(0.285)	(0.225)	(0.100)	(0.122)	(0.149)
Average hours in Regular Month	0.30	21.11	6.34	0.83	1.61	2.68
N	38936	39656	39188	39608	39596	39644

The results are estimated by OLS. $\top$: Estimating equation using equation (2.5). $\perp$: Estimating equation using equation (2.4).Regressions control for a set of individual and household characteristics (see 2.2) and month, survey year and district fixed effects. Standard errors clustered at the woreda level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.4.3 Effect of Precipitation Shock by Shock Severity

The severity of the precipitation shock may play an important role. In the sense that a precipitation shock, z, equal to one will not have the same effect as a precipitation shock, z equal to three. Hence, to have a stronger reference group and to examine the magnitudes of shocks on a comparative basis, Table B.1 in the Appendix takes into account the severity of the precipitation shocks. I show the impacts of 0.5 standard deviations wide bins, with the bin set by $z \in (-1, 1)$ as the reference category (see Figure 2.5). The effect is separated by gender. Panel A in Table B.1 displays the results on time allocation for women, while Panel B those for men. The effects observed in Table 2.6 are mostly determined by medium and extreme intensity shocks. For women, a very severe precipitation shortage ($z < -1.5$) reduces the time allocated to attend an unpaid traineeships and casual public work. For men on the other hand, a very severe precipitation shortage (with $z < -2.5$) reduces the time spent in unpaid traineeships as well as time spent in casual public works.

There is evidence of significant gender differences in time spent attending unpaid traineeships (significant decline for women relative to men, p-value = 0.00). A (medium intensity) surplus of precipitation ($z > 1.5$) is associated with an increase in the time spent in unpaid traineeships for women. However, a severe positive precipitation shock ($z > 2.5$), decreases the time spent in in household chores and unpaid traineeships by women. On the other hand, a severe positive precipitation shock decreases the time spent in non-agricultural work, work for wage/salary and unpaid traineeships for men. I find evidence of gender difference in the effect of severe positive shocks on time allocation to work for wage/salary by men relative to women (p-value = 0.065).

Table 2.7: Effect of Lagged Precipitation Shock on Time Allocation to Labour Activities

	(1) Household chores	(2) Agricultural work	(3) Non Agriculture work	(4) Casual Public work	(5) Work for wage Salary	(6) Unpaid Traineeship
PANEL A: WOMEN						
Precipitation Shock (ξ)	-0.00946	-0.425*	0.185	0.0189*	-0.159	-0.0520*
	(0.0213)	(0.172)	(0.141)	(0.0484)	(0.0636)	(0.0340)
Lag (2months)	-0.0317	0.304	-0.328	0.112*	0.227**	-0.0716
	(0.0259)	(0.204)	(0.194)	(0.0519)	(0.0870)	(0.0991)
Lag (4months)	0.0185	0.0524	0.120	-0.0403	-0.0574	-0.0698
	(0.0225)	(0.164)	(0.163)	(0.0409)	(0.0526)	(0.0826)
Mean hours in Regular Month	1.33	9.48	11.35	0.56	0.52	1.95
N	38714	38654	38558	38858	38870	38870
R^2	0.180	0.317	0.569	0.114	0.164	0.397
PANEL B: MEN						
Precipitation Shock (ξ)	-0.00955	-0.150	-0.020**	0.0161**	-0.0580	-0.0219
	(0.00989)	(0.199)	(0.146)	(0.0659)	(0.0683)	(0.0980)
Lag (2months)	0.0141*	-0.152	0.0651	0.0451	0.0469	0.0113
	(0.0127)	(0.252)	(0.181)	(0.0739)	(0.0842)	(0.106)
Lag (4months)	-0.00341	0.380	0.132	-0.0376	0.0231	-0.0458
	(0.0111)	(0.198)	(0.158)	(0.0568)	(0.0763)	(0.0813)
Mean hours in Regular Month	0.30	21.11	6.34	0.83	1.61	2.68
N	38936	39656	39188	39608	39596	39644
R^2	0.155	0.410	0.310	0.113	0.170	0.331

The results are estimated by OLS.Estimating equation using equation (2.6).Regressions control for a set of individual and household characteristics (see 2.2) and month, survey year and district fixed effects. Standard errors clustered at the woreda level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.4.4 Effect of Lagged Precipitation Shock on Time Allocation

Table 2.7 shows the results using equation (2.7) including 2-month lagged monthly precipitation shocks. I display the results for women in Panel A while the results for men are presented in Panel B. For women, an occurring precipitation shock significantly reduces the time allocation to unpaid traineeships and agricultural work, and significantly increases the time allocation to casual public works. The two-month lagged precipitation shock has a consistent and statistically significant effect on time allocation into increases casual public works and work for a salary/wage. For men, an occurring precipitation shock increases time allocated to casual public works, but significantly reduces the time spent non-agricultural work. The lagged effects are however weak and the only effect is that a 2-month lagged precipitation increases the time allocated to household chores.

Additionally, the evidence shows gender based responses to precipitation shocks to time allocated to particular activities. Indeed, a two-month lagged precipitation shock leads to a significantly greater change in time spent in casual public work (p-value = 0.000) and work for wage/salary (p-value =0.001) for women relative to men. Furthermore, and in line with the results given in Table (2.6), an occurring precipitation shock leads to a significantly higher change in time spent in to casual public works by women relative to men, (p-value = 0.003). Finally, a four-month lagged precipitation shock is not statistically significant.

When the effects of precipitation shortage and precipitation surplus and their lagged effects are separated (see Table 2.8), I find that an occurring negative shock (precipitation shortage) significantly increases the time allocation by women to casual public works. Note that a 2-month lagged precipitation shortage significantly decreases allocation of time to casual public works. For men, a 4-month lagged negative precipitation shock reduces the time allocated to unpaid traineeship. Change in time allocated casual public works in response to a two-month precipitation shortage lag is significantly greater for women compared to men (p-value = 0.002). A four-month lagged negative precipitation shock has a significantly greater effect on time allocated to unpaid traineeship (p-value = 0.001) by men relative to females.

Table 2.8: Effect of Lagged Precipitation Shock on Time Allocation to Labour Activities: 2 months and 4 months lags

	(1) Household chores	(2) Agricultural work	(3) Non Agriculture work	(4) Casual Public work	(5) Work for wage Salary	(6) Unpaid Traineeship
PANEL A: WOMEN						
Positive Shock (ξ^{+})	-0.0331	-0.00191	0.197	-0.0715	0.0341	0.225
	(0.0543)	(0.420)	(0.380)	(0.119)	(0.126)	(0.241)
Negative Shock (ξ^{-})	-0.0739	0.400	-0.0914	0.134*	0.225	-0.0629
	(0.0668)	(0.427)	(0.363)	(0.111)	(0.153)	(0.225)
Positive Precipitation Shock Lag (2months)	0.0104	-0.251	-0.255	0.0473	0.0523	-0.483
	(0.0700)	(0.535)	(0.498)	(0.136)	(0.153)	(0.301)
Negative Precipitation Shock Lag (2months)	0.146	-0.405	0.589	-0.202**	-0.322	-0.0904
	(0.0803)	(0.529)	(0.486)	(0.143)	(0.191)	(0.296)
Positive Precipitation Shock Lag (4months)	-0.0275	0.173	0.181	0.0400	-0.168	-0.103
	(0.0549)	(0.400)	(0.379)	(0.0951)	(0.102)	(0.221)
Negative Precipitation Shock Lag (4months)	-0.0542	0.152	-0.463	0.0975	0.0937	0.113
	(0.0579)	(0.400)	(0.371)	(0.117)	(0.130)	(0.240)
Mean hours in Regular Month	1.33	9.48	11.35	0.56	0.52	1.95
N	38714	38654	38558	38858	38870	38870
R^2	0.180	0.317	0.569	0.114	0.164	0.398
PANEL B: MEN						
Positive Shock (ξ^{+})	-0.0390	-0.565	-0.168	0.0780**	-0.177	-0.113
	(0.0246)	(0.469)	(0.387)	(0.133)	(0.175)	(0.228)
Negative Shock (ξ^{-})	0.0234	-0.281	0.148	-0.0525	0.0143	0.0355
	(0.0248)	(0.498)	(0.384)	(0.176)	(0.206)	(0.263)

The results are estimated by OLS.Estimating equation using equation (2.7).Regressions control for a set of individual and household characteristics (see 2.2) and month, survey year and district fixed effects. Standard errors clustered at the woreda level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Effect of Lagged Precipitation Shock on Time Allocation to Labour Activities: 2 months and 4 months lags II

	(1) Household chores	(2) Agricultural work	(3) Non Agriculture work	(4) Casual Public work	(5) Work for wage Salary	(6) Unpaid Traineeship
PANEL A: MEN						
Positive Precipitation Shock Lag (2months)	0.0492	0.0194	-0.0102	-0.181	-0.156	0.102
	(0.0335)	(0.629)	(0.516)	(0.180)	(0.255)	(0.300)
Negative Precipitation Shock Lag (2months)	-0.0492	0.971	-0.0549	0.00985	-0.0952	0.393
	(0.0409)	(0.629)	(0.498)	(0.228)	(0.278)	(0.318)
Positive Precipitation Shock Lag (4months)	-0.00587	0.647	0.269	0.103	0.312	-0.484
	(0.0268)	(0.496)	(0.403)	(0.155)	(0.223)	(0.240)
Negative Precipitation Shock Lag (4months)	0.00991	-0.799	0.0415	0.0698	0.0559	-0.644**
	(0.0374)	(0.481)	(0.392)	(0.181)	(0.231)	(0.236)
Mean hours in Regular Month	0.30	21.11	6.34	0.83	1.61	2.68
N	38936	39656	39188	39608	39596	39644
R^2	0.155	0.410	0.310	0.113	0.170	0.332

The results are estimated by OLS.Estimating equation using equation (2.7).Regressions control for a set of individual and household characteristics (see 2.2) and month, survey year and district fixed effects. Standard errors clustered at the woreda level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.4.5 Interactions of Precipitation shocks with Survey Month

In this section, I consider the variation in precipitation shocks over the season months. Figure 2.8 presents the impacts for October to April. This period represents the belg season, which is the crucial period for crop grain agriculture in Ethiopia. Every point on Figure 2.8 shows the additional impact on time allocation to a particular activity in a month marked by a precipitation shock, compared to a normal month[13] and the corresponding 95% confidence intervals. The most considerable impact in adjustment to time allocation is to casual public works and unpaid traineeships. For both men and women, a precipitation shock in February, the beginning of the belg season, significantly increases the time devoted to casual/part-time labour. The effects are large at approximately 20 percentage points. The estimated impact on time allocation to unpaid traineeship activities is also quite large. For men, a precipitation shock in February is associated with a 9% percentage point decline in time allocation to unpaid traineeship and a 11% percentage point decline for women.

A precipitation shock in March is also associated with reduced time allocation to wage/salary work and household chores for men. On the other hand, for women, a precipitation shock in October increases the time spent on household chores.

Figure B.1 in the Appendix separates the effects of positive and negative precipitation shocks on time allocation to the different labour activities. A positive rainfall shock in February leads to a positive and statistically significant increase in the time allocated to casual/part-time activities, for men and women. For women, a negative rainfall shock in February is associated with a large and statistically significant increase in casual public works and household chores and a substantial reduction in time allocation to an unpaid traineeship. A negative precipitation shock in February creates a considerable

[13] This is captured by $\alpha_{1m} + \alpha_{3m}$ in equation (2.8).

reorganisation in the time spent in various activities, especially for women.

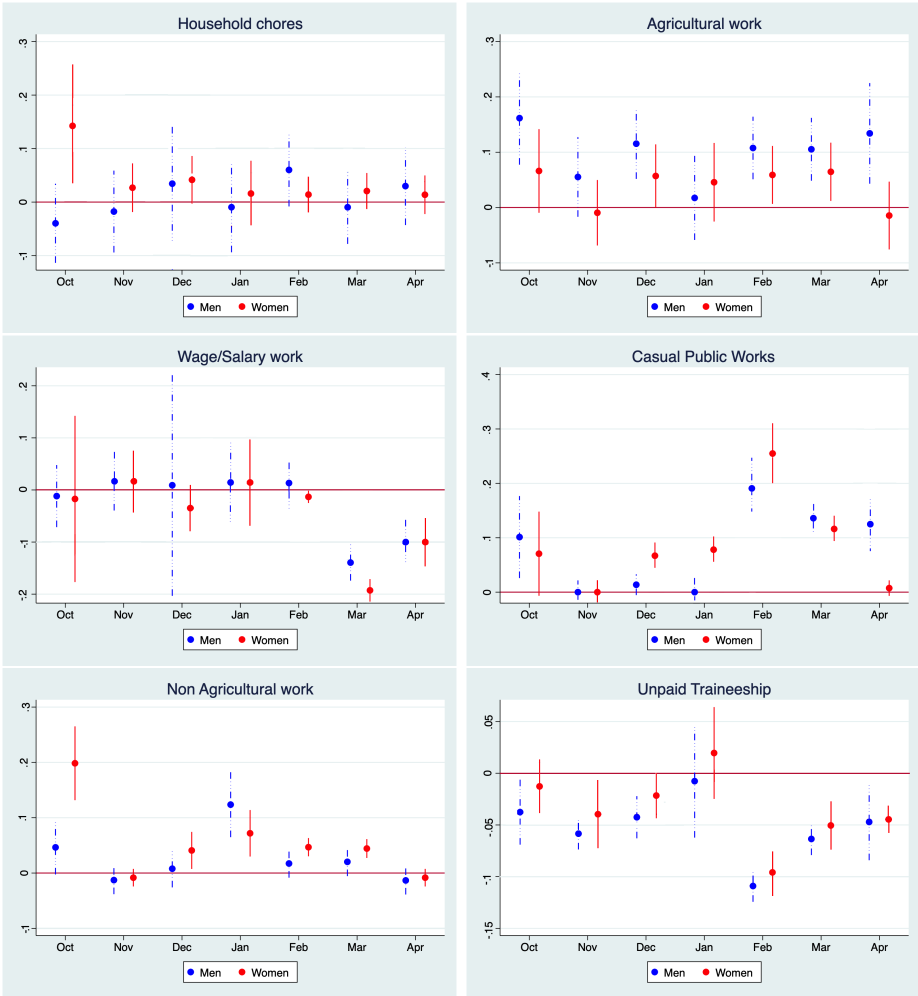


Figure 2.8: Effect of any Precipitation Shock by Sex, Activity and Survey Month

Note: Regression specifications are given by equation (2.8). Coefficient estimates and 95% C.I of the difference estimate $\alpha_2 + \alpha_{3m}$ presented. The regressions includes controls for a set of individual and household characteristics(religion, marital status, household size and monthly per capita household expenditure) and is restricted to individuals aged 15-60. Regressions also control for district and year dummies. Precipitation shocks are defined in Section 2.2.2. The reference month is October.

The results show slightly smaller effects for men. A precipitation shortage in February reduces time allocation to an unpaid traineeship and increases in allocated time to casual public works.

These results indicate the importance of casual public work, which is dominated by PSNP work, in rural Ethiopia. PSNP acts as a programme of employer-of-last-resort in rural Ethiopia (Hirvonen and Hoddinott, 2020). Figure 2.4 shows that February is an important month in the Ethiopian cropping calendar. It includes the planting season for major crops and cereals, which is dominated by rural smallholder farmers. Hirvonen and Hoddinott (2020) suggests that demand for work under PSNP and casual public work is the highest in the months of mid-January to mid-June. This is in line with the average time allocation by men and women in PSNP and casual public work across months in Figure 2.2. The results reveal that rural households use casual public work (or PSNP work) as insurance against agricultural (productivity) shocks.

2.5 Heterogeneous Impacts of Precipitation Shocks

2.5.1 Rainfed vs Irrigated Woredas

In this section, I follow the strategy in Sarsons (2011) and introduce systems of irrigation (i.e. the building of dams) to assess heterogeneous impacts of precipitation shocks on time allocation to the different labour activities. For this purpose, I split the sample into rain fed woredas and woredas with irrigated systems and run separate regressions for these two type of woredas.

Table 2.9 presents the responses on time allocation to the different labour activities to precipitation shocks. This regression results use the specification given by equation (2.4) separately for the woredas with irrigated system and the rain fed woredas. Each column corresponds to a different regression.

The results suggest that, the negative effect of precipitation shock on time allocated to unpaid traineeships consistently observed and reported in Tables 2.6-B.1, seem to be determined by the response in rain fed districts. An agricultural productivity shock in rain fed district leads to a significant decrease in the time spent engaging in unpaid traineeships by women. This leads to a considerable negative effect on human capital accumulation. These effects are not observed in districts that have irrigated systems. Moreover,

Table 2.9: Heterogeneous effects: Rain fed vs Irrigated woredas (Precipitation shocks)

	Rainfed		Irrigated	
	Female	Male	Female	Male
	(1)	(2)	(3)	(4)
Household chores	-0.0198	-0.00152	-0.0224	0.00480
	(0.00596)	(0.0154)	(0.0194)	(0.00987)
Agricultural work	-0.196*	0.0180	0.108	0.0971
	(0.0944)	(0.110)	(0.168)	(0.179)
Non Agriculture work	0.0153	-0.0388	-0.0483	-0.0435
	(0.0870)	(0.0884)	(0.144)	(0.136)
Casual Public work	-0.0145	-0.0182	0.000950	0.0462
	(0.0251)	(0.0306)	(0.0561)	(0.0809)
Work for wage/Salary	-0.0101	-0.0124	0.00779	0.0272
	(0.0313)	(0.0361)	(0.0473)	(0.0828)
Unpaid Traineeship	-0.0183*	-0.0756	-0.122	0.0674
	(0.0233)	(0.0438)	(0.135)	(0.109)

Coefficient estimate of Precipitation shock (ξ) from OLS regressions. Separate regressions for rainfed and irrigated woredas and each row displays the results from a distinct regression.Regressions control for a set of individual and household characteristics (see 2.2) and month, survey year and district fixed effects.Standard errors clustered at the woreda level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

a precipitation shock in a rain fed district leads to an increase in the time spent in household chores. Table 2.10 reports the regression results for men and women in rain fed districts versus districts with irrigated systems, using equation (2.5). In line with previous results, most of the variation on time allocation to different labour activities is driven by rain-fed districts. This is observed for both men and women. In response to both a positive and negative precipitation shock, males and females in rain fed districts decrease their time allocation to unpaid traineeships, leading to adverse impacts on human capital accumulation. In turn, in response to negative precipitation shocks, females in rain fed districts increase their time allocation to casual public works.

Table 2.10: Heterogeneous effects: Rainfed vs Irrigated districts (Positive and Negative Precipitation Shocks)

	Negative Precipitation Shock (ξ^-)				Positive Precipitation Shock (ξ^+)			
	Rainfed		Irrigated		Rainfed		Irrigated	
	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Household chores	0.00217	-0.00789	0.0234	-0.0188	-0.0530	0.00207	-0.0201	-0.00384
	(0.0495)	(0.0185)	(0.0453)	(0.0233)	(0.0349)	(0.0139)	(0.0484)	(0.0263)
Agricultural work	0.411	0.0390	-0.269	-0.274	-0.117	-0.0252	-0.0213	-0.0618
	(0.266)	(0.314)	(0.376)	(0.386)	(0.221)	(0.274)	(0.440)	(0.492)
Non Agriculture work	0.0450	0.196	0.0745	0.0852	0.176	0.0413	0.0352	-0.0259
	(0.226)	(0.238)	(0.312)	(0.302)	(0.235)	(0.234)	(0.418)	(0.363)
Casual Public work	0.0190**	-0.00637	0.00927	-0.0297	-0.0599	-0.108	-0.0369	0.0132
	(0.0868)	(0.122)	(0.101)	(0.174)	(0.0676)	(0.0866)	(0.147)	(0.254)
Work for wage/Salary	0.0380	0.0575	0.0445	-0.0173	0.0167	0.00153	-0.00559	0.0883
	(0.0648)	(0.0967)	(0.0975)	(0.152)	(0.0660)	(0.0846)	(0.151)	(0.225)
Unpaid Traineeship	0.0282	0.184	0.158	-0.246	-0.0451**	-0.109**	-0.567	-0.758
	(0.0688)	(0.131)	(0.270)	(0.237)	(0.0569)	(0.113)	(0.377)	(0.289)

Positive and negative Precipitation shocks as defined in Section 2.2.2. Separate regressions for rainfed and irrigated woredas and each row displays the results from a distinct regression. Regressions control for a set of individual and household characteristics (see 2.2) and month, survey year and district fixed effects.Standard errors clustered at the woreda level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.5.2 Rainfed vs Irrigated woredas, by Severity of Shock

Table B.4 in Appendix B looks at the impact of precipitation shocks by the severity of shocks. The effects for women (Panel A) are strongest when $z > 1.5$. In a rainfed district, a strong positive precipitation shock reduces the time allocated to household chores, casual public works and unpaid traineeships. However, a strong positive precipitation shock is associated with an increase in time allocated to wage/salary work. For males in a rainfed district, a shock with $-2.5 < z < -1$, leads to a reduction in unpaid traineeships. However, most of the effect is found for $z > 1.5$ and is associated with a reduction in time allocated to agricultural activities, casual public works, wage/salary work and unpaid traineeships. On the other hand, a mild to severe positive precipitation shock is associated with an increase in time allocated to other non-agricultural work. In districts with irrigation, there are no effects of extreme weather shocks on the time allocated to different labour activities for both gender, suggesting that precipitation shocks are more prone to cause variations in rain-fed districts.

2.6 Conclusion

Female and male adults use different time allocation of labour strategies in response to exogenous precipitation shocks. Generally, I find that precipitation shortages result in females increasing their time allocation to casual public works and reducing time in unpaid traineeships. Males in contrast, respond to negative precipitation shocks by increasing their time in regular wage/salary work. A positive precipitation shock leads to both males and females reducing the time allocated to unpaid traineeships. These responses to precipitation shocks may be intended to insure household units against changes in consumption or incomes.

There are several key insights that I feature. To begin with, families do adjust their labour allocations across different labour activities as a response to precipitation shocks. Secondly, a month-to-month analysis of precipitation shocks is crucial given that, in farming family units, labour allocation responses seem to differ by the the month of the shock. Failing to consider these monthly variations, increases the risk of missing out on crucial circumstantial keystones of household labour time allocation decisions. Lastly, infrastructure shows improving impacts on agricultural productivity shocks. The heterogeneous consequences of precipitation shocks in rainfed districts, as opposed to districts with irrigated systems, and specifically the negative consequences on human capital in rainfed districts, have far-achieving costs. Evidently, the right system of irrigation (i.e. dams) enables a significant contribution into protecting rural incomes in the event of adverse shocks.

I find evidence of declining time allocation to attending education institutions by men and women in response to precipitation shocks. This possibly affects their chances for human capital accumulation, which in turn, could have potential negative long-run consequences for their welfare. Because variations in labour allocations in response to precipitation shocks are usually short-run responses, there could be long-run implications of not attending educational institutions. An avenue for policy would be to increase the incentives of individuals enrolled in education institutions to remain in school in the event of adverse weather shocks. This could be done through monetary transfers to help ensure that education is not significantly affected by the household experiencing a precipitation shock. The monetary transfer could provide short-run liquidity for consumption smoothing, and could also help to guarantee education progress.

In terms of policy implementation, the timing in this context is very important. Mainly, weather shocks in February/March lead to the most significant changes in household labour allocations for both men and women. This is because Ethiopian agriculture is mostly rain-fed and that the production is more prone to be impacted by adverse precipitation shocks, eventually causing men and women to change their labour activities as a response. The availability of labour under Casual Public Works (PW) during this time is key to allow-ing households insure against weather shocks, especially in rain-fed districts. Woredas authorities should be ready to arrange and channel support into making extra work available during this period to help protect households against shocks effectively.

Ultimately, suitable infrastructure may play an important role. Indeed, systems of irrigation such as dams store water during times of precipitation shortage and enable to protect against surplus rain by impounding water in reservoirs. By regulating the water flow, dams thus protect agricultural production in the dam-fed irrigation districts against fluctuations stemming from precipitation shocks. As a result, the agricultural production in the dam-fed irrigation districts should be more stable, and incomes of households should be less volatile.

The variability in precipitation that is more and more related to climate change indicates that new risk mitigation strategies may be needed to face the current climate regime. Therefore, it is necessary to establish empirically whether government interventions can help households adapt to increased risks due to climatic change. Notably, government interventions must be many-sided to account for the various means households use to respond to agricultural productivity shocks. Government policies that encourage individuals to continue in school/college or remain in the labour market are of vital importance. Lastly, it is imperative to invest in the right infrastructure that can act as an ex-ante insurance mechanism. Government policies, appropriately established, can play a significant role in protecting household welfare and additionally improving economic growth.

Chapter 3

Determinants of Child Mistreatment: Evidence from Ivory Coast

3.1 Introduction

Child mistreatment is a documented public health and social problem that raises an important challenge to development. According to the World Health Organization (WHO), child mistreatment includes all forms of physical, sexual, emotional ill-treatment and neglect involving child labour and exploitation (WHO, 2016). Previous research has found mistreated children face long-term negative health and developmental consequences (Norman et al., 2012), and encounter immune and nervous system problems (Harris et al., 2014), as well behavioral issues such as substance abuse, drinking and criminal activities (Gilbert et al., 2009). Maltreated children are also vulnerable to depressive disorders (Coates and Messman-Moore, 2014), and intimate partner violence in adulthood (Afifi et al., 2017).

Ivory Coast is a West African country highly dependent on its agriculture. It is also the largest producer and exporter of cocoa beans in the world. A number of qualitative studies in limited geographical areas show that children in Ivory Coast are at high risk for violence at home, in the community, and schools (Merrill et al., 2020; Blay-Tofey and Lee, 2015). According to these studies, there is a widespread and accepted nature of violence against children, making child mistreatment a particular concern for the country. According to UNICEF, among children aged 2-14 years, 87% of them are victims of emotional violence and 21% victims of severe corporal punishment.

However, due to data limitations, up to date, no studies have been conducted with the required rigour and methodology to generate nationally representative data on the true burden and prevalence of violence against children and its risk factors in Ivory Coast.

Kwnoledge on the factors that contribute to higher risks of physical and emotional ill-treatment is of great interest for policymaking. This chapter sheds light on the household characteristics that drive different forms of child mistreatment including child abuse in Ivory Coast. To do this, the chapter uses the first Ivorian nationally representative household survey that includes a component of discipline methods applied by caregivers to their children and hazardous forms of child labour. While the paper is descriptive, the correlative evidence on the household characteristics of child mistreatment should help decision-makers identify households at high risk of child mistreatment and enable prevention.

The empirical results reveal that household wealth is an important protective factor against child abuse in Ivory Coast. Children with higher economic status are less likely to experience emotional abuse than children from poorer households. Females in particular have a higher risk of experiencing extreme physical abuse. I also observe a higher risk of child mistreatment among children living in rural areas. Moreover, the results confirm the fact that children who are not living with their biological parents, referred to as independent children, receive a more unfavourable treatment. In particular, I find evidence that independent children have higher risks of experiencing emotional and mild physical abuse.

The content of the rest of the paper is as follows. Section 3.2 provides a literature review on child abuse and neglect. Section 3.3 is dedicated to the data. Sections 3.4 and 3.5 present the methodology and the results, respectively. Section 3.6 is devoted to robustness checks of the main results and finally section 3.7 concludes.

3.2 Literature review

In this section I review what is known about the determinants of child mistreatment including child abuse and exploitative child labour, drawing on theoretical and empirical studies and I discuss how this study relates to the current literature.

3.2.1 Child Abuse

Notwithstanding numerous media reports incidents on child mistreatment, detailed analyses of the contributing risk and protective factors of child emotional and physical abuse from a nationwide representative sample, in developing countries are rare.

To date, the economic literature lists very few studies of child abuse and those that exist focus mainly on developed countries. Markowitz and Grossman (1998) and Markowitz and Grossman (2000) use American data on physical violence in families, along with data on drug and alcohol prices and taxes to examine the relationship between the demand for alcohol and intra-household violence rate toward children. The authors find that both the probability and the amount of violence committed depend on the price of alcohol and illegal drugs, and the parent, child and household characteristics. They argue that there exists a significant negative relationship between alcohol prices and parental physical violence toward children, especially with regards to violence committed by mothers. These papers do not address the more extensive links between socioeconomic factors, economic policies, and child mistreatment.

In contrast, Paxson and Waldfogel (1999, 2002, 2003) provide more insight into these relationships by using state-level panel data to study long-term relationships between parental and household characteristics (including the presence or absence of fathers), state-level socioeconomic variables, as well as state-level measures of child mistreatment. They observe a positive relationship between poverty and child abuse.

Brooks-Gunn and Duncan (1997) argue that poverty or large changes in income may influence the likelihood that parents will engage in abuse or neglect over and above the influence of a family's overall level and source(s) of income. In particular, decreases in income may lead to a deterioration of the home environment or quality of parental care, and to an increase in parental stress. Additionally, families experiencing persistently low income may be at greater risk to engage in harsher, more punitive, and less responsive parenting, and provide lower quality home environments than their higher-income counterparts or those experiencing only brief or episodic periods of low income, as the adverse effects of low income may accumulate over time (McLoyd, 1998).

The family structure is also an essential factor to consider. Paxson and Waldfogel (2003) report a positive relationship between child abuse and fathers' absence in single-parent families with working mothers. However, their study only uses macro data such that their finding can, therefore, not be tested at the household level. Moreover, non-biological parents may have fewer incentives than biological parents to invest in children. In fact, research argues that the disutility received from child mistreatment may vary by decision-makers. One direct consequence is that when decision-makers do not think about the adverse effects of child mistreatment on child development, child mistreatment rates rise.

3.2.2 Exploitative Child Labour

Most of the empirical evidence on child mistreatment from developing countries focuses on exploitative child labour. For example, Bhalotra (2002), measures parental altruism using the consumption ratio of tobacco and child-specific products such as clothing and footwear in rural Pakistan and finds that parental altruism relates to lower rates of child labour. Edmonds and

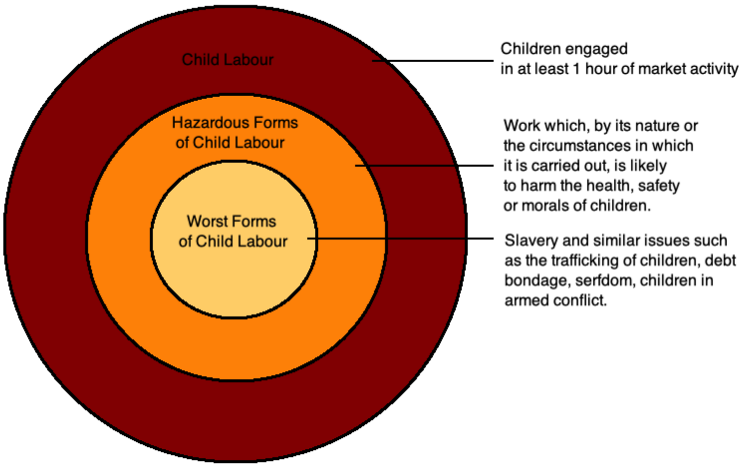


Figure 3.1: Definitions of Child Labour, Hazardous and Worst Forms of Child Labour, by ILO.

Shrestha (2012) and Kamei (2018) study children without parental care and present a detailed analysis of the relationship between child labour and children living without their biological parents. In their research, they define a child living away from his biological parents as an "Independent child".

Edmonds (2010) finds that children employed as porters and rag pickers display a high incidence of paternal's disability and less ownership of farmland. DeGraff et al. (2014) and Kamei (2018) have both studied household characteristics of children working in hazardous environments using large-scale representative data sets. DeGraff et al. (2014) investigates the children in several hazardous industries using Brazilian data, while Kamei (2018) uses Nepalese data. In line with Edmonds (2010), the authors predict that the absence of parents increases the transition into hazardous forms of child labour, but their estimation results fail to find any statistically significant effect of household productive asset, such as land and livestock.

The above point is interesting because Bhalotra and Heady (2003), observe that households with higher wealth indices (measured by household characteristics such as household materials, sanitation level or ownership of assets) are responsible for more child labour. They argue that wealth assets, including agricultural land or livestock, raise the household labour demand for child labour. In a similar way, Cockburn and Dostie (2007) find more child labour from households with more livestock or cropland in Ethiopia. Edmonds (2010) finds a greater number of rag pickers and porters, jobs classified as worst forms of labour, from households who do not own land in Nepal. Hence, while cropland and livestock ownership raises child labour, children may be shielded from entering hazardous labour because productive household assets provide safer working environments for children.

3.2.3 How this study relates to the current literature

Previous research on child abuse hence omits several essential questions related to the relationship between poverty, household characteristics and child abuse. This paper offers empirical evidence to identify better the household characteristics that drive the selection into child abuse in a context of extreme poverty. The identification of those households that are at high risk of child mistreatment may hold implications for the establishment of preventive policies, and for ensuring that such policies are put in place early. In the spirit of Edmonds and Shrestha (2012), and Kamei (2018), I classify independent children and consider children living with close relatives from independent children living with "other relatives". Children who migrated to the household of close relatives may be exposed to fewer agency issues than children living with distant relatives. This is because distant relatives have weaker interfamilial relationships than closer relatives.

3.3 Data

I use data from the Multiple Indicator Cluster Survey (MICS) from Ivory Coast, a household survey that focuses on the health and welfare of women and children in developing countries, following the Millennium Development Goals and other international mother and child health goals. With the technical and financial support of UNICEF, the government of Ivory Coast carries out this survey every three to five years. The fifth round of data collection (MICS5) was conducted in 2016 and includes a household questionnaire, a questionnaire for women aged 15 to 49, and a questionnaire for primary caregivers of children under five. The unit of analysis that guided the data collection is the household member and particularly individuals five years of age and over. The survey covers many aspects of welfare, including education, child labour, child discipline, mortality and health. This data is the first nationally representative survey that includes a module on child discipline[1]. Section 3.3.1 describes the module in more detail.

3.3.1 Child Discipline Module: Data and Descriptive Statistics

The child discipline module of MICS5 contains questions concerning discipline practices applied by primary caregivers to their children in the month before the survey. The child discipline module is based on questions from the Murray A Straus Parent-Child Conflict Tactics Scale, a questionnaire for measuring domestic abuse, including domestic violence against children[2].[3] For this study, I create a binary outcome variable: "child abuse" if the child experiences any form of abuse. That is, I classify those respondents who responded "Yes" to any of the questions as practicing child abuse and those who answered "No" to all questions as "no abuse". Later in the study I create three binary outcomes that specify each type of abuse experienced: (i) emotional abuse, (ii) mild and (iii) extreme physical abuse (see Table 3.1).

Table 3.2 presents the descriptive statistics of individuals' and households' characteristics by whether the child experienced any form of abuse or not[4]. Column 1 shows that 33% of children experience some form of abuse.

UNICEF calculates the household wealth score variable through a principal component analysis (PCA). It is a composite index composed of many

[1] Section 3.6.2 in the robustness checks uses data from the child labour module and provides an analysis on hazardous child labour, which is another focus in child development.

[2] The module was applied to children aged between 2 and 14 years, and only one child is randomly chosen if more than one child is in this age group.

[3] I am only using this information for children aged 6 to 14 years.

[4] I present the definitions of the variables used in Table C.2 in the Appendix.

Table 3.1: Child discipline module's questions regarding psychological and physical abuse

Emotional Abuse
Screamed, shouted at him/her?
Called him/her stupid, lazy or another name
Mild Physical Abuse
Shook him/her?
Spanked, hit or slapped him/her on the bottom with bare hand?
Hit or slapped him/her on the hand, arm or leg?
Extreme Physical Abuse
Hit or slapped him/her on the face, head or ears?
Hit him/her on the bottom or elsewhere on the body with a hard object like a belt?
Beat him/her up with a device (repeatedly hit as hard as possible)?

observable household characteristics such as household materials, sanitation level or asset ownership. It is calculated separately for urban and rural areas to avoid any urban bias. Compared with other income measures, the asset index is regarded as better information to capture the long-term household wealth level, particularly in developing countries. It represents a more permanent status, is more easily measured (with only a single respondent needed in most cases) and needs fewer questions than either consumption expenditures or income (Macro, 2004).

From the descriptive statistics, we observe that the household wealth score is highly related to child abuse status. The mean differences between the child abuse and no child abuse, in columns 4 shows that the wealth level is higher for non-abused children. This suggests that poverty not only result but also causes child abuse. Table C.2 in the appendix shows that out of 2774 independent children, 2274 (82 per cent) experience abuse compared to 2444 (or 21 per cent) non independent children (out of 11573)[5] Figure 3.2 shows that approximately 19 per cent of children are independent children who live away from their

[5] A 2×2 contingency table analysis was conducted to evaluate whether the variable Abuse (Yes, No) was associated with the variable Independent (Yes, No). The analysis yielded a Pearson chi-square (1, N = 14347) = 3754.92, which is greater than the critical value of 3.85. Thus, the null hypothesis of no association was rejected ($p < .05$).

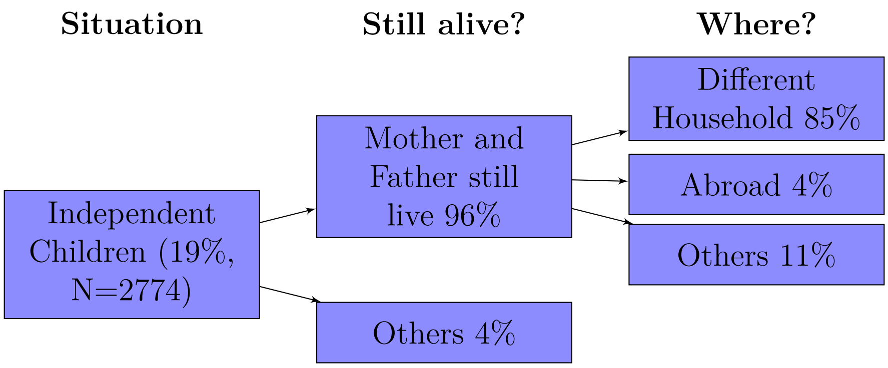


Figure 3.2: Independent Children: Parental Situation.

biological parents. Among them, 96 per cent still have both parents alive, the remaining reports that either one or both parents are deceased. For those 96 per cent, the majority (85 per cent) report that both parents are still in Ivory Coast but live in a different household. This suggests that these children have left the households where they were born. The remaining 15 per cent report that one of their parents are either abroad or somewhere else in Ivory Coast. Since MICS5 does not provide with information on the original households for independent children, in this study I consider children to be integrated into their destination household once they have migrated. This assumption seems well founded, as the majority of independent children reside in the household of a relative.

Figure 3.3 gives details on the relationship of independent children to the household head. Among independent children, around 41 per cent are the grandson/daughter of the household head. Around 9 per cent of the children reported the absence of their father and 32 percent the absence of their mother. In 7 per cent of the cases, the father is still alive whereas he is deceased in 2 per cent of the cases. Mothers are alive in 28 per cent of the cases and deceased in 4 per cent of the cases.Table C.3 in the appendix shows that the percentage of a deceased father is slightly greater among physically abused children (7%) compared to non-abused children (6%). Moreover, 30% of children experiencing extreme physical abuse reported that their mother away, compared to only 27% of non abused children.

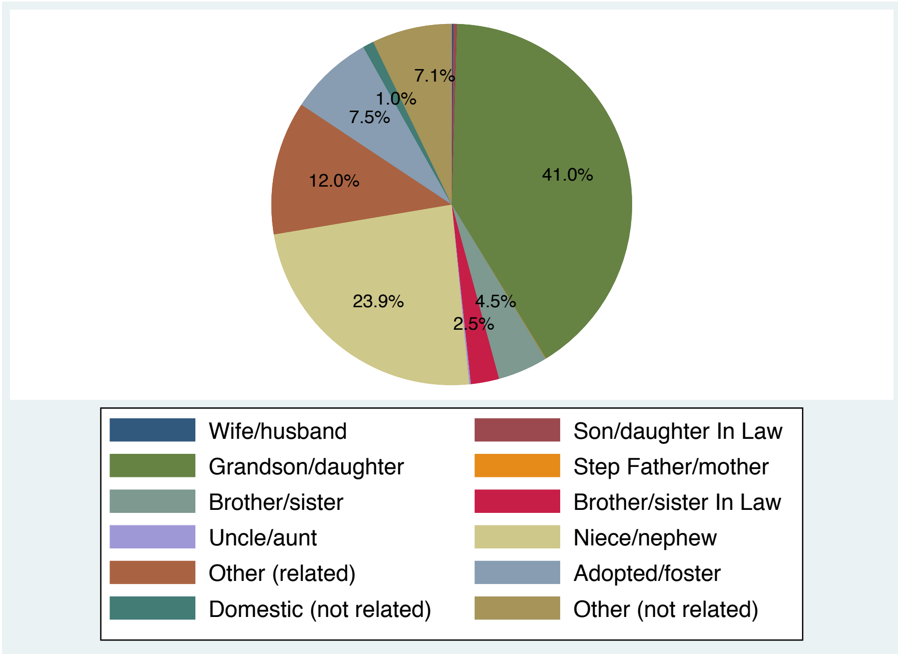


Figure 3.3: Relationship to Head of Household for Independent Children

3.3.2 Limitations of the data

One limitation of the data is the underreporting bias. This is because respondents in an interview tend to underreport the prevalence of child mistreatment due to stigmatization or fear of disclosing incidents of violence, the prevalence of child abuse and neglect is likely to be higher than what is reported (Edmonds, 2010). While there is a concern for the underreporting issue, especially in child abuse and neglect, there are a significant number of cases of child abuse and children involved in hazardous forms of child labour in this paper.

3.4 Methodology

In this section, I outline the methodology used to identify the determinants of child abuse and I present the empirical results.

To examine the determinants of child abuse, I conduct a logistic regression analysis. The model studies three outcomes; emotional abuse, mild physical abuse, extreme physical abuse. Figure 3.4 presents the logit model. I run multiple specifications of the model: the first specification in column (1) includes

Table 3.2: Descriptive Statistics

	Total (1)	No Abuse (2)	Any Abuse (3)	MEAN DIFF (3) vs (2) (4)	Min-Max (5)
Child Abuse	0.33				0-1
Enrolled	0.73 (0.44)	0.74 (0.44)	0.73 (0.45)	0.02 (0.01)	0-1
Wealth Index	2.78 (1.35)	2.83 (1.34)	2.55 (1.30)	0.28 (0.02)***	1-5
Female	0.49 (0.50)	0.49 (0.50)	0.49(0.50)	0.00 (0.01)	0-1
Age	9.66 (2.57)	9.89 (2.63)	9.60 (2.55)	0.29 (0.05)***	6-14
Rural	0.69 (0.46)	0.64 (0.48)	0.71 (0.45)	-0.08 (0.01)***	0-1
Household size	7.97 (3.98)	8.49 (4.64)	7.84 (3.78)	0.67 (0.08)***	2-45
<5 years (#)	1.51 (1.37)	1.46 (1.41)	1.29 (1.14)	1.50 (0.01)**	0-8
6-14 years (#)	3.17 (1.89)	3.17 (2.12)	3.18 (1.83)	-0.01 (0.04)	1-11
>60years (#)	0.33 (0.64)	0.35 (0.66)	0.32 (0.63)	0.02 (0.01)	0-5
Head (Female)	0.16 (0.37)	0.15 (0.35)	0.17 (0.37)	-0.02 (0.01)**	0-1
Head (age)	48.65 (12.91)	49.60 (13.48)	48.41 (12.75)	1.19 (0.23)***	17-98
Land(hectares)	8.23 (18.86)	7.89 (17.42)	8.31 (19.21)	-0.42 (0.39)	0-99
Livestock	2.17 (10.68)	2.62 (12.43)	2.06 (10.18)	0.60 (0.22)**	0-99
Horse/Donkey	0.15 (3.47)	0.11 (2.38)	0.16 (3.70)	-0.05 (0.07)	0-99
Chicken	6.87(14.96)	6.39 (13.76)	6.99 (15.25)	-0.60 (0.33)	0-99
Has electricity	0.55 (0.50)	0.61 (0.49)	0.53 (0.50)	0.08 (0.01)***	0-1
Has access to water	0.16 (0.36)	0.19 (0.39)	0.15(0.36)	0.04 (0.01)***	0-1
Independent child	0.19 (0.39)	0.05 (0.07)	0.48 (0.27)	-0.43(0.32)**	0-1
Father away	0.02 (0.13)	0.02 (0.14)	0.02 (0.13)	0.00 (0.00)	0-1
Father dead	0.07 (0.25)	0.06 (0.24)	0.07 (0.25)	-0.01 (0.00)	0-1
Mother away	0.28 (0.45)	0.27 (0.44)	0.28 (0.45)	-0.01 (0.00)*	0-1
Mother dead	0.04 (0.19)	0.03 (0.16)	0.04 (0.19)	-0.01 (0.00)**	0-1
N	14347	9629	4718		

age[6] and region fixed controls (μ). Column (2) controls for the household liv-

[6]The regressions include a vector of dummy variables (γ) for age in all specification. The tables do not display the coefficients for the age dummies. However, the results show that

Table 3.3: Abuse among Independent Children

	Any Abuse	**No Abuse**	Total
Independent	2274	500	2774
Non Independent	2444	9129	11573
Total	4718	9629	14347

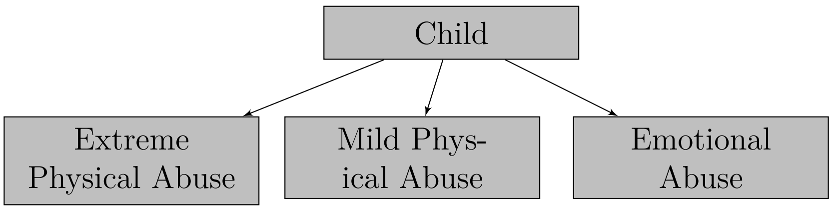


Figure 3.4: Logit model for child abuse

ing standard, by adding the wealth index (W). Column (3) controls for some household characteristics (H); i.e. the number of children and dependent members, and column (4) includes home production assets (L); for e.g. hectares of land and livestock ownership. Column (5) introduces an interaction term for households in which the child's biological grandparents take the role of the household head (INT1). The baseline group is boys with both father and mother present. Column (6) adds interactions for girls to study gender differences in the effect of parents' absence (INTS). The full list of explanatory variables is presented in Table C.2. The full logit model is described by:

$$ln\frac{p}{(1-p)} = \beta_0 + \beta_1 X + \beta_2 W + \beta_3 H + \beta_4 L + \beta_5 INT1 + \beta_6 INTS + \gamma + \mu + \varepsilon \tag{3.1}$$

where p is the probability of the outcome of interest (see Figure 3.4). All regressions include region fixed effects, controlling for common regional factors such as regional labour market conditions. Standard errors are clustered at the household level to account for correlation in errors at this level. Note that the result tables show the marginal effects and represent the percentage points increase or decrease in the probability of falling in each category. The discrete

the likelihood of children experiencing abuse increases with age. When the age is controlled by a linear relationship, a 1-year increase in age increases child abuse by approximately 2 percentage points.

variables demonstrate a change from zero to one, and I estimate the continuous variables at the mean value.

3.5 Empirical Results

Table 3.4 presents the results from the logistic regression analysis on child abuse. First, an increase in the wealth score decreases the likelihood of experiencing any form of abuse. This finding supports the hypothesis of Brooks-Gunn and Duncan (1997) that household wealth is an important protective factor against child abuse. Children with a higher economic status are on average 12 percentage points less likely to experience emotional abuse than children from poorer households. Table 3.5 looks closely at the type of abuse children experience and displays two specifications per abuse type. Table 3.5 reveals that children from poorer households are 16% more likely to experience emotional abuse and 12% mild and extreme physical abuse compared to children from wealthier households. The results confirm that poverty is a chronic problem in Ivory Coast and permeates several aspect of the society and family, including children's welfare.

I also find gender differences in that females are more at risk to be abused. For example, Table 3.5 reveals that females are on average 14% more likely to experience emotional and extreme physical abuse compared to male children. This result contrasts that of Atteraya et al. (2018), who finds that males in Nepal are more at risk of acts of physical abuse. This could be explained by the fact that Ivory Coast is a very patriarchal society in which females hold a subordinate position within their households and often find themselves at the mercy of men (Stichter and Parpart, 1988). The coefficient signs for independent children is positive and statistically significant. In terms of percentage change, the full model shows that the probability for independent children versus other children to experience abuse is 17%. Table 3.5 shows that the coefficients on emotional, mild and extreme physical abuse are positive and statistically significant at the 5 per cent level. In terms of percentage change, the probabilities for independent children versus non-independent children to experience emotional, mild and extreme physical abuse are 14%, 29% and 7%, respectively. These results corroborate that of Case et al. (2004) who shows that children who are not living with their biological parents are treated unfavourably. They argue that the closeness of biological ties governs altruistic behaviour.

Finally, Table C.4, the full table in the Appendix, shows that households with more children and dependent members (less than 5 years old and more than 65 years old) are associated with higher risk of child abuse. This may reflect the fact that more dependent members may lead to more parental (household head) role stress and depression, more authoritarian parent-to-child interactions and greater use of physical punishment. I also find that the absence of the father is not a significant determinant of child abuse in Ivory Coast. However, children with their biological mother absent because of death have a higher risk of experiencing abuse. One explanation for this result may be because mothers are considered to be the persons with the greatest interest in children's health and survival, and with the greatest willingness to devote time to their protection and to care for them in sickness (Caldwell and Caldwell, 1993). A mother's death could thus leave the child to be more vulnerable to abuse. Even though the interaction of independent children living with grandparents is not statistically significant, the results show that including the interaction term in the model slightly increases the coefficient for independent children from approximately 15.5 percentage points to 16.1 percentage points. The observation that children who live with distant families are more prone to experience abuse is in line with the assumption that the disutility of agent is relevant to the selection into child abuse. Finally, I observe a higher risk of each type of abuse among children living in rural areas and no significant effect of household productive assets.

Table 3.4: Logit Regression Analysis on Child Abuse

	Child abuse					
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0855***	0.0745***	0.0119**	0.0106**	0.0104**	0.0104***
	(0.0449)	(0.0424)	(0.0424)	(0.0423)	(0.0420)	(0.0419)
Rural	0.219***	0.0995***	0.0662***	0.0524***	0.0521***	0.0515***
	(0.0569)	(0.0623)	(0.0630)	(0.0636)	(0.0636)	(0.0636)
Household size	0.0386***	0.0362***	0.150***	0.154***	0.154***	0.154***
	(0.00483)	(0.00490)	(0.0106)	(0.0107)	(0.0107)	(0.0107)
Independent	0.145***	0.147***	0.160***	0.155**	0.161**	0.167*
	(0.0813)	(0.0813)	(0.0826)	(0.0827)	(0.0828)	(0.0843)
Wealth Index		-0.149***	-0.124***	-0.122***	-0.122***	-0.122***
		(0.0300)	(0.0303)	(0.0303)	(0.0303)	(0.0303)
N	14347	14347	14347	14347	14347	14347

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Column (1) includes age and region fixed controls (μ). Column (2) controls for the household living standard by adding the wealth index (W). Column (3) controls for some household characteristics (H), i.e. the number of children and dependent members, and column (4)includes home production assets (L), e.g. hectares of land and livestock ownership. Column (5) introduces an interaction term for households in which the child's biological grandparents take the role of the household head (INT1). The baseline group is boys with both father and mother present. Column (6) adds interactions for girls to study gender differences in the effect of parents' absence (INTS). The full list of explanatory variables is presented in Table C.2.

Table 3.5: Logit Regression Analysis on Child Abuse by the type of Abuse

	Emotional Abuse		Mild Physical Abuse		Extreme Physical Abuse	
	(1)	(2)	(1)	(2)	(1)	(2)
Female	0.0141***	0.0135***	0.0563	0.0066	0.0136***	0.0155***
	(0.0404)	(0.0428)	(0.0347)	(0.0368)	(0.0401)	(0.0423)
Rural	0.0402**	0.0386**	0.053**	0.0533**	0.0633***	0.0631***
	(0.0609)	(0.0609)	(0.0525)	(0.0525)	(0.0626)	(0.0627)
Household size	0.133***	0.133***	0.0879***	0.0881	0.0366***	0.0370***
	(0.0104)	(0.0104)	(0.00871)	(0.00871)	(0.00966)	(0.00967)
Independent	0.140**	0.147**	0.291***	0.296***	0.0616***	0.0626***
	(0.0798)	(0.0814)	(0.0682)	(0.0690)	(0.0808)	(0.0819)
Wealth Index	-0.159***	-0.159***	-0.122***	-0.121***	-0.116***	-0.115***
	(0.0289)	(0.0289)	(0.0247)	(0.0247)	(0.0280)	(0.0280)
N	14347	14347	14347	14347	14347	14347

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Column (1) includes age and region fixed controls (μ), wealth index (W), household characteristics, home production assets (L) and an interaction term for households in which the child's biological grandparents take the role of the household head (INT1). The baseline group is boys with both father and mother present. Column (2) adds interactions for girls to study gender differences in the effect of parents' absence (INTS). The complete list of explanatory variables is presented in Table C.2.

3.6 Robustness Checks

In this section, I perform two robustness checks of the results. I first conduct the analysis using a distinct estimation technique. That is, I use a Linear Probability Model (LPM) to estimate child abuse. I then consider the participation in hazardous child labour as another form of child abuse.

3.6.1 Linear Probability Model

The results on the LPM estimation of child abuse are displayed in Table 3.6. Table 3.7 shows the results focusing on each form of child abuse, i.e., emotional, mild and extreme physical child abuse. The results confirm the findings from the main analysis as all coefficients have the same sign and are similar in magnitude.

3.6.2 Hazardous Child Labour

Child abuse is defined as "the intentional, non-accidental injury, maltreatment of children by parents, caretakers, employers or others including those individuals representing governmental or non-governmental bodies which may lead to temporary or permanent impairment of their physical, mental and psycho-social development, disability or death" (NIPCCD, 1988). Therefore, Caeser-Leo (1999) argues that forced hazardous child labour by caregivers or employers, which leads to intentional, accidental or non-accidental long-term injury, and which results in impairment of the child's health, safety, or morals, can thus be considered a serious form of child abuse and neglect. In this section, I check the robustness of the results using the participation in hazardous child abuse as an alternative definition of child abuse. I use data from the module on child labour in MICS5.

Table C.9 presents the first stage of the sequential logit model on child labour. At this stage, households choose between child labour or not; Child labour is defined as 1 if the child is working at least one hour in market activity and 0 otherwise. Table C.10 presents the key results focusing on the second stage of the sequential logit model, the selection into hazardous forms of child labour among working children. Amongst children engaged in child labour, independent children have a higher probability of working in hazardous work by around sixty percentage points across all specifications. The mean prevalence of hazardous child labour is 20 per cent (see Table C.1, column 1 in the Appendix C), therefore the sixty percentage points increase to 80 per cent in hazardous forms of child labour, ultimately a rise of 75 per cent.

The interaction of children living with their grandparents remains insignificant.All other coefficients show a similar trend with the main analysis, except for female which is negatively related to the incidence of child labour and hazardous child labour. Moreover, the number of hectares of land owned by the household is now statistically significant, and the effect of the ownership of livestock negatively impacts the participation in hazardous child labour.

A summary statistics of this data and additional results on hazardous child labour are presented in Appendix C.

Table 3.6: Robustness Checks: LPM Regression Analysis on Child Abuse

	Child Abuse					
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0770***	0.0652***	0.0190***	0.0163***	0.0160***	0.0224***
	(0.0673)	(0.0673)	(0.0668)	(0.0657)	(0.0638)	(0.00635)
Rural	0.374***	0.0176***	0.0132***	0.0310***	0.0409***	0.0608***
	(0.173)	(0.0156)	(0.0154)	(0.0176)	(0.0187)	(0.0207)
Household size	0.0676***	0.0632***	0.252***	0.256***	0.256***	0.256***
	(0.0910)	(0.0092)	(0.0171)	(0.0173)	(0.0173)	(0.0173)
Independent	0.0242**	0.0246**	0.0259**	0.0249**	0.0258**	0.0268*
	(0.0133)	(0.0133)	(0.0133)	(0.0133)	(0.0133)	(0.0135)
Wealth Index		-0.0241***	-0.0202***	-0.0201***	-0.0201***	-0.0201***
		(0.00492)	(0.00491)	(0.00491)	(0.00491)	(0.00491)
N	14347	14347	14347	14347	14347	14347

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Column (1) includes age and region fixed controls (μ). Column (2) controls for the household living standard by adding the wealth index (W). Column (3) controls for some household characteristics (H), i.e. the number of children and dependent members, and column (4)includes home production assets (L), e.g. hectares of land and livestock ownership. Column (5) introduces an interaction term for households in which the child's biological grandparents take the role of the household head (INT1). The baseline group is boys with both father and mother present. Column (6) adds interactions for girls to study gender differences in the effect of parents' absence (INTS). The complete list of explanatory variables is presented in Table C.2.

Table 3.7: Robustness Checks: LPM Regression Analysis on Child Abuse by type

	Emotional Abuse		Mild Physical Abuse		Extreme Physical Abuse	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.00225	0.00484	0.0136	0.0141	0.0237***	0.0290***
	(0.00700)	(0.00739)	(0.00816)	(0.00864)	(0.00705)	(0.00751)
Rural	0.839	0.00811*	0.0119	0.0115	0.0487**	0.0101**
	(0.111)	(0.0111)	(0.0125)	(0.0125)	(0.0104)	(0.0104)
Household size	0.0241***	0.0240***	0.0205***	0.0206***	0.00595***	0.00601***
	(0.00181)	(0.00181)	(0.00195)	(0.00195)	(0.00157)	(0.00157)
Independent	0.0389**	0.0420**	0.0243**	0.0212**	0.0116**	0.0334**
	(0.0138)	(0.0139)	(0.0164)	(0.0166)	(0.0138)	(0.0140)
Wealth Index	-0.0285***	-0.0286***	-0.0280***	-0.0277***	-0.0196***	-0.0193***
	(0.00513)	(0.00513)	(0.00582)	(0.00582)	(0.00477)	(0.00477)
N	14347	14347	14347	14347	14347	14347

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Column (1) includes age and region fixed controls (μ). Column (2) controls for the household living standard by adding the wealth index (W). Column (3) controls for some household characteristics (H), i.e. the number of children and dependent members, and column (4)includes home production assets (L), e.g. hectares of land and livestock ownership. Column (5) introduces an interaction term for households in which the child's biological grandparents take the role of the household head (INT1). The baseline group is boys with both father and mother present. Column (6) adds interactions for girls to study gender differences in the effect of parents' absence (INTS). The complete list of explanatory variables is presented in Table C.2.

3.7 Conclusion

This research examines the determinants that drive child abuse, using the fifth round of the Ivory Coast Multiple Indicator Cluster Survey (MICS5).

The empirical results reveal that household wealth is an important protective factor against child abuse in Ivory Coast. Children from wealthier households are less likely to experience emotional abuse compared to children of lower economic status families. Females have a higher risk of experiencing extreme physical abuse and I observe a higher risk of child mistreatment among children living in rural areas. Moreover, the results tend to suggest that

Table 3.8: Sequential Logit Model on Child Labour and Hazardous Forms of Labour

	First Stage Sequential Logit					
	Child Labour					
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.116**	-0.115**	-0.102*	-0.0965*	-0.0974*	-0.126**
	(0.0399)	(0.0401)	(0.0404)	(0.0405)	(0.0405)	(0.0423)
Rural	0.634***	0.610***	0.625***	0.564***	0.564***	0.564***
	(0.123)	(0.119)	(0.121)	(0.121)	(0.121)	(0.121)
Household size	0.00669	0.0141	0.0355	0.0270	0.0268	0.0269
	(0.0122)	(0.0133)	(0.0204)	(0.0208)	(0.0208)	(0.0209)
Independent	0.0361	0.102	-0.0043	-0.0032	-0.00042	-0.0002
	(0.0684)	(0.0687)	(0.0708)	(0.0710)	(0.0709)	(0.0715)
Wealth Index		-0.281***	-0.302***	-0.302***	-0.301***	-0.302***
		(0.0401)	(0.0402)	(0.0401)	(0.0401)	(0.0401)
N	14347	14347	14347	14347	14347	14347

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Column (1) includes age and region fixed controls (μ). Column (2) controls for the household living standard by adding the wealth index (W). Column (3) controls for some household characteristics (H), i.e. the number of children and dependent members, and column (4)includes home production assets (L), e.g. hectares of land and livestock ownership. Column (5) introduces an interaction term for households in which the child's biological grandparents take the role of the household head (INT1). The baseline group is boys with both father and mother present. Column (6) adds interactions for girls to study gender differences in the effect of parents' absence (INTS). The complete list of explanatory variables is presented in Table C.2.

children who are not living with their biological parents receive unfavourable treatment. Indeed, I find evidence that independent children have higher risks of experiencing emotional and mild physical abuse.

Furthermore, the results show that the inclusion of an interaction for children living with their grandparents, increases slightly the coefficient for independent children. This is in line with the assumption that the disutility of agent is relevant to child abuse.

Most child mistreatment programmes focus on victims or perpetrators of child abuse and neglect. Only a few stress prevention approaches that aim at preventing child abuse and neglect from happening in the first place. In terms of preventive policy recommendation, policies aiming at identifying, supporting and monitoring children who cannot be cared for by biological parents or discouraging unnecessary foster placement of children should help reduce risk for exposure to violence, abuse, neglect, and exploitation.

The findings of the study are robust and generalizable to the population. Nonetheless, the study has some limitations related to the underreporting of child mistreatment due to stigmatization or fear of disclosing incidents of violence. The prevalence of child abuse and neglect is likely to be higher than what is reported.

Appendix A

Chapter 1

Table A.1: Gold Boom effect on Children Outcome by gender: Participation

	Male					Female				
	(1) Economic	(2) Domestic Chores	(3) Not attending	(4) School Attainment	(5) School Lag	(6) Economic	(7) Domestic Chores	(8) Not attending	(9) School Attainment	(10) School Lag
Price	0.00873	-0.0333	0.00192	0.00974	-0.00262	0.213***	-0.145***	-0.00326	0.0470***	-0.0254***
	(0.0120)	(0.0245)	(0.00232)	(0.0103)	(0.00473)	(0.0130)	(0.0149)	(0.00863)	(0.00800)	(0.00612)
Price× ASM Area	0.168***	-0.175***	-0.0255	0.0367*	-0.0603	-0.0126	0.0435	-0.0290	-0.0642*	0.0342**
	(0.0205)	(0.0458)	(0.0456)	(0.0148)	(0.00754)	(0.0356)	(0.0297)	(0.0150)	(0.0321)	(0.0130)
Price× LSM Area	-0.109	0.0152	0.0205	0.0460	-0.0115	-0.0294	0.00438	0.00507	0.0321	-0.0110
	(0.0700)	(0.0519)	(0.0194)	(0.0268)	(0.0204)	(0.0636)	(0.0266)	(0.0280)	(0.0166)	(0.0158)
ASM Area	-1.150***	1.176***	0.266	-0.226*	0.365***	0.0147	-0.367	0.162	0.335	0.256**
	(0.143)	(0.266)	(0.257)	(0.0931)	(0.0491)	(0.219)	(0.190)	(0.0895)	(0.183)	(0.0778)
LSM Area	0.793	-0.143	-0.162	-0.309	0.0940	0.276	0.0385	-0.0459	-0.197	0.0706
	(0.475)	(0.365)	(0.127)	(0.177)	(0.126)	(0.433)	(0.169)	(0.164)	(0.104)	(0.102)
N	5249	5249	5249	5249	5249	5125	5125	5125	5125	5125
R^2	0.113	0.084	0.641	0.442	0.434	0.221	0.142	0.657	0.473	0.379

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include district and year fixed effects, and individuals and households' controls, which include: individual's age and gender, household head's age and gender, literacy, asset, size, access to water and electricity; as well as an indicator of the household area.

Table A.2: Gold Boom effect on Child Labour by gender: Hours

	All		Female		Male	
	Economic Hours	Domestic Hours	Economic Hours	Domestic Hours	Economic Hours	Domestic Hours
	(1)	(2)	(3)	(4)	(5)	(6)
Price	0.953	-1.805	4.367***	-6.559***	0.287	-0.891
	(0.666)	(1.161)	(0.654)	(0.533)	(0.278)	(0.632)
Price × ASM Area	0.759	-2.097	1.888	2.385	1.610**	-3.811***
	(0.631)	(1.189)	(0.776)	(1.538)	(0.551)	(0.537)
Price × LSM Area	-2.060	-4.284	-3.386	-3.801	-3.148	-1.282
	(1.963)	(1.386)	(1.776)	(1.326)	(2.376)	(1.240)
ASM Area	-9.195*	13.34	8.518	-18.50*	-14.79***	26.75***
	(4.087)	(7.378)	(4.901)	(9.304)	(3.602)	(3.521)
LSM Area	15.77	27.94**	23.46*	25.86**	23.66	7.481
	(13.10)	(8.795)	(11.57)	(8.547)	(16.23)	(8.079)
N	10374	10374	5125	5125	5249	5249
R^2	0.088	0.157	0.098	0.209	0.102	0.110

Notes: standard errors in parentheses. Standard errors are clustered at district level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The Gold Boom measure is the interaction between the presence of (large-scale) artisanal in the (20 km) 10km vicinity of the households and the logarithm of international gold prices. All regressions include district and year fixed effects, and individuals and households' controls, which include: individual's age and gender, household head's age and gender, literacy, asset, size, access to water and electricity; as well as an indicator of the household area.

Table A.3: Spreading the labour: interaction with having Siblings

	(1) Economic Work	(2) Domestic Chores	(3) Not attending	(4) School Attainment	(5) School Lag
No sibling	-0.00849	0.0000332	0.0128	0.0223	-0.0166
	(0.0156)	(0.0152)	(0.0140)	(0.0154)	(0.00972)
No sibling × ASM Gold Boom	-0.0154	-0.00809	0.00601	-0.00205	0.000505
	(0.0127)	(0.0144)	(0.0110)	(0.0128)	(0.00803)
No sibling × LSM Gold Boom	0.00869	0.0121	0.00648	-0.00947	0.000761
	(0.00944)	(0.00902)	(0.00711)	(0.00868)	(0.00523)
N	10374	10374	10374	10374	10374
R^2	0.128	0.187	0.111	0.181	0.187

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include district and year fixed effects, and individuals and households' controls, which include: individual's age and gender, household head's age and gender, literacy, asset, size, access to water and electricity; as well as an indicator of the household area. ASM Gold Boom is the measure of Price × ASM Area. LSM Gold Boom corresponds to Price × LSM Area.

Table A.4: Spreading the labour: interaction with being the Eldest

	(1) Economic Work	(2) Domestic Chores	(3) Not attending	(4) School Attainment	(5) School Lag
Being the eldest	0.0246	0.0270	0.0122	0.00925	-0.0142
	(0.0129)	(0.0122)	(0.0114)	(0.0124)	(0.00857)
Being the eldest × ASM Gold Boom	0.00525	-0.00714	-0.00405	-0.00489	-0.00105
	(0.00879)	(0.00864)	(0.00825)	(0.00885)	(0.00657)
Being the eldest × LSM Gold Boom	-0.0112	0.00396	0.00922	0.0144	0.000606
	(0.00653)	(0.00603)	(0.00573)	(0.00638)	(0.00449)
N	10374	10374	10374	10374	10374
R^2	0.129	0.188	0.109	0.177	0.187

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The Gold Boom measure is the interaction between the presence of (large-scale) artisanal in the (20 km) 10km vicinity of the households and the logarithm of international gold prices. All regressions include district and year fixed effects, and individuals and households' controls, which include: individual's age and gender, household head's age and gender, literacy, asset, size, access to water and electricity; as well as an indicator of the household area. ASM Gold Boom is the measure of Price × ASM Area. LSM Gold Boom corresponds to Price × LSM Area.

Table A.5: Spreading the labour: interaction with having a Sister(s)

	(1) Economic Work	(2) Domestic Chores	(3) Not attending	(4) School Attainment	(5) School Lag
Female					
Have sister(s)	-0.00146	0.000404	0.000802	0.000668	-0.000552
	(0.000564)	(0.000521)	(0.000514)	(0.000563)	(0.000364)
Have sister(s) × ASM Gold Boom	-0.0316	0.00242	-0.0339	-0.0771	0.0149
	(0.00580)	(0.00601)	(0.00638)	(0.00635)	(0.00495)
Have sister(s) × LSM Gold Boom	-0.000225	0.00876	-0.00140	-0.00377	0.00254
	(0.00456)	(0.00396)	(0.00411)	(0.00472)	(0.00307)
N	5125	5125	5125	5125	5125
R^2	0.192	0.155	0.088	0.155	0.154
Male					
Have sister(s)	-0.00924	-0.00552	-0.0113	-0.0000138	-0.00598
	(0.0162)	(0.0161)	(0.0146)	(0.0158)	(0.0106)
Have sister(s) × ASM Gold Boom	0.00940	-0.00732**	-0.00359	0.00416**	-0.00149
	(0.0131)	(0.0137)	(0.0115)	(0.0135)	(0.00895)
Have sister(s) × LSM Gold Boom	0.0303	-0.0299	-0.000604	-0.00132	-0.00373
	(0.00922)	(0.00941)	(0.00824)	(0.00940)	(0.00612)
N	5249	5249	5249	5249	5249
R^2	0.107	0.128	0.105	0.148	0.206

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include district and year fixed effects, and individuals and households' controls, which include: individual's age and gender, household head's age and gender, literacy, asset, size, access to water and electricity; as well as an indicator of the household area. ASM Gold Boom is the measure of Price × ASM Area. LSM Gold Boom corresponds to Price × LSM Area.

Table A.6: Education of Head of household

	(1) Economic Work	(2) Domestic Chores	(3) Not attending	(4) School Attainment	(5) School Lag
ASM Boom × Years of Head Education	0.00786	-0.00142	-0.00356*	0.00244	-0.00380
	(0.00623)	(0.00597)	(0.00731)	(0.00618)	(0.00526)
LSM Boom × Years of Head education	-0.00183	0.00840	0.00180	-0.00426	-0.000416
	(0.00417)	(0.00373)	(0.00412)	(0.00343)	(0.00302)
Years of Head education	-0.0280***	-0.000578	-0.0227***	0.0671***	-0.0142***
	(0.00446)	(0.00445)	(0.00438)	(0.00420)	(0.00347)
Artisanal Boom	0.0560***	0.0676	0.00246*	-0.0161***	-0.00130
	(0.00483)	(0.00479)	(0.00448)	(0.00486)	(0.00330)
LSM Boom	-0.0878	0.00197	-0.00244	-0.00284	0.00416
	(0.00349)	(0.00328)	(0.00308)	(0.00351)	(0.00230)
N	10246	10246	10246	10236	10246
R^2	0.128	0.187	0.111	0.180	0.186

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The measure of artisanal Boom is the interaction between ln(gold price) and ASM area. The LSM boom measure is the interaction between ln(gold price) and LSM area. All regressions include district and year fixed effects, and individuals and households' controls, which include: individual's age and gender, household head's age and gender, literacy, asset, size, access to water and electricity; as well as an indicator of the household area.

A.1 Mining Communes Population Growth

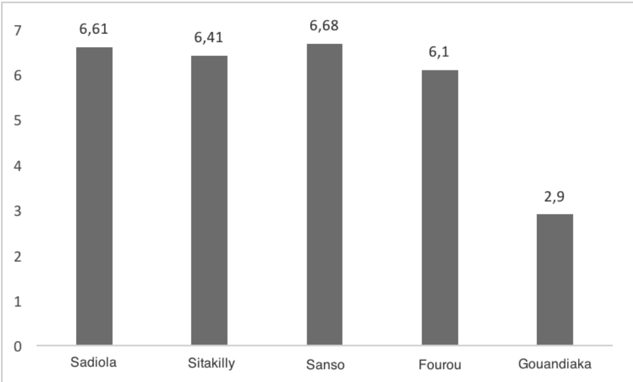


Figure A.1: Population growth rate for mining communes. 1998-2009. Sanoh and Massaoly (2015).

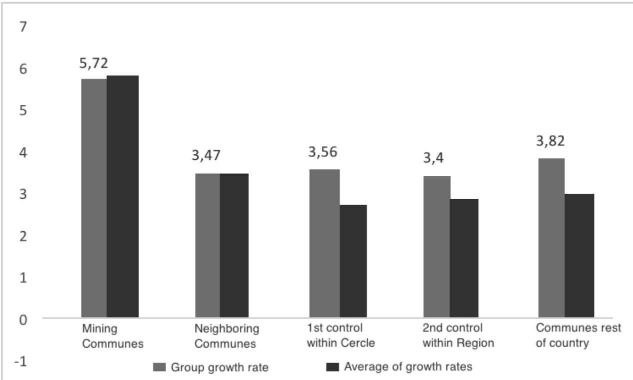


Figure A.2: Population growth rate by group of communes. 1998-2009. Sanoh and Massaoly (2015)

Appendix B

Chapter 2

B.1 Effect of Precipitation Shocks on Time Allocation to Labour Activities: by shock severity

Table B.1: Precipitation Shocks on Time Allocation to Labour Activities: by shock severity

	(1) Household chores	(2) Agricultural work	(3) Non Agriculture work	(4) Casual Public work	(5) Work for wage Salary	(6) Unpaid Traineeship
PANEL A: WOMEN						
$z < -3.5$	-0.156	3.874	1.067	-0.179	0.569	-1.176***
	(0.146)	(4.081)	(2.537)	(0.121)	(2.006)	(0.206)
$-3.5 < z < -3$	-0.156	3.859	1.049	-0.184	0.572	-1.155***
	(0.247)	(6.940)	(4.325)	(0.182)	(3.415)	(0.314)
$-3 < z < -2.5$	-0.108	3.695	0.890	-0.188	0.547	-0.975**
	(0.175)	(4.735)	(2.950)	(0.134)	(2.327)	(0.306)
$-2.5 < z < -2$	0.224	0.574	0.229	0.200	0.0389	0.0357
	(0.267)	(1.282)	(0.881)	(0.368)	(0.283)	(0.635)
$-2 < z < -1.5$	0.0225	0.1000	-0.0390	-0.0109**	0.0178	-0.517**
	(0.110)	(0.555)	(0.421)	(0.122)	(0.171)	(0.191)
$-1.5 < z < -1$	0.000353	0.0923	0.0594	0.0356	0.00491	0.0419
	(0.0339)	(0.238)	(0.206)	(0.0607)	(0.0689)	(0.130)
$1 < z < 1.5$	-0.0346	0.0260	0.150	-0.0788	-0.0288	-0.444
	(0.0381)	(0.274)	(0.263)	(0.0669)	(0.0879)	(0.138)
$1.5 < z < 2$	-0.0616	-0.00150	0.233	0.137	-0.0922	0.102**
	(0.0530)	(0.343)	(0.382)	(0.148)	(0.0819)	(0.219)
$2 < z < 2.5$	-0.0614	-0.0859	-0.110	-0.0338	-0.0450	-0.329
	(0.0664)	(0.632)	(0.699)	(0.166)	(0.165)	(0.341)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Effect of Precipitation Shocks on Time Allocation to Labour Activities: by shock severity (continued II)

	(1) Household chores	(2) Agricultural work	(3) Non Agriculture work	(4) Casual Public work	(5) Work for wage Salary	(6) Unpaid Traineeship
$2.5 < z < 3$	-0.448***	-2.993	2.828	1.438	-0.100	-0.928***
	(0.101)	(1.917)	(4.323)	(1.670)	(0.295)	(0.175)
$z > 3$	-0.162	-0.667	-0.341	0.0839	-0.0301	-1.031*
	(0.135)	(0.914)	(1.454)	(0.155)	(0.0683)	(0.471)
Mean hours in Regular Month	1.33	9.48	11.35	0.56	0.52	1.95
N	38714	38654	38558	38858	38870	38870
R^2	0.180	0.317	0.569	0.114	0.164	0.398
PANEL B: MEN						
$z < -3.5$	-0.0222	-0.402	-0.769	-2.117***	-0.410**	-2.089***
	(0.0282)	(2.959)	(1.318)	(0.413)	(0.149)	(0.248)
$-3.5 < z < -3$	-0.0216	-0.388	-0.795	-2.118***	-0.403	-2.055***
	(0.0443)	(5.016)	(2.225)	(0.426)	(0.221)	(0.372)
$-3 < z < -2.5$	-0.0217	-0.397	-0.789	-2.120***	-0.406*	-2.083***
	(0.0327)	(3.586)	(1.593)	(0.416)	(0.170)	(0.283)
$-2.5 < z < -2$	0.0101	0.0813	0.331	0.0503	-0.173	-0.119
	(0.121)	(1.132)	(0.882)	(0.338)	(0.441)	(0.754)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Effect of Precipitation Shocks on Time Allocation to Labour Activities: by shock severity (continued III)

	(1) Household chores	(2) Agricultural work	(3) Non Agriculture work	(4) Casual Public work	(5) Work for wage Salary	(6) Unpaid Traineeship
$-2 < z < -1.5$	-0.00603	-0.488	0.265	-0.121	-0.0373	-0.518
	(0.0304)	(0.643)	(0.430)	(0.181)	(0.191)	(0.294)
$-1.5 < z < -1$	-0.0151	0.0346	0.110	0.0702	-0.00885	-0.0154
	(0.0154)	(0.266)	(0.211)	(0.0963)	(0.115)	(0.140)
$1 < z < 1.5$	-0.00392	-0.0375	0.0442	-0.0695	-0.0453	-0.447**
	(0.0152)	(0.314)	(0.243)	(0.107)	(0.133)	(0.157)
$1.5 < z < 2$	-0.0336	-7.976	-5.382	-0.610	-0.961	-1.837*
	(0.0556)	(4.599)	(5.375)	(1.075)	(1.162)	(0.931)
$2.5 < z < 3$	-0.0105	-0.733	0.704	0.000411	-0.449*	-0.462
	(0.0550)	(1.368)	(1.536)	(0.147)	(0.207)	(0.848)
$z > 3$	-0.0428	-1.526	-4.466**	-0.203	-0.789**	-1.124***
	(0.206)	(3.432)	(1.429)	(0.196)	(0.298)	(0.310)
Mean hours in Regular Month	0.30	21.11	6.34	0.83	1.61	2.68
N	38936	39656	39188	39608	39596	39644
R^2	0.156	0.410	0.310	0.113	0.170	0.332

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B.2 Precipitation Shock by Sex, Activity and Survey Month

B.3 Heterogeneous effects: Rainfed vs Irrigated districts

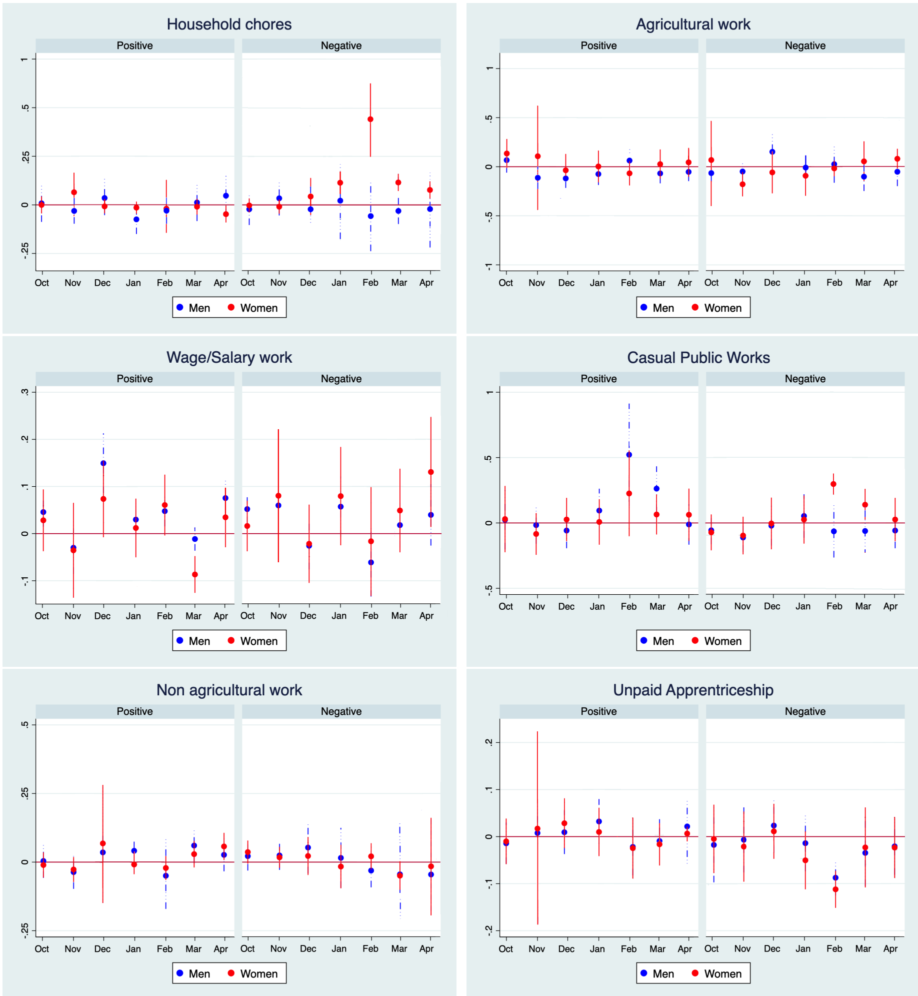


Figure B.1: Effect of any Precipitation Shock by Sex, Activity and Survey Month

Note: Regression specifications are given by equation (2.9). Coefficient estimates and 95% C.I of the difference estimate $\alpha_2 + \alpha_{3m}$ presented. The regressions includes controls for a set of individual and household characteristics(religion, marital status, household size and monthly per capita household expenditure) and is restricted to individuals aged 15-60. Regressions also control for village and year dummies. Positive and negative shocks are defined in Section 2.2.2.

Table B.2: Heterogeneous effects: Rainfed vs Irrigated districts (Lagged versus contemporaneous Precipitation)

	Household chores		Agricult.		Non Agricult.		Casual Public		Wage/Salary		Unpaid Traineeship	
	Rain	Irrig.	Rain	Irrig.	Rain	Irrig.	Rain	Irrig.	Rain	Irrig.	Rain	Irrig.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PANEL A: WOMEN												
Negative	-0.11	-0.0354	0.284	0.405	-0.201	0.240	0.103	0.251	0.219	0.23	0.208	-0.28
	(0.09)	(0.071)	(0.535)	(0.673)	(0.443)	(0.608)	(0.136)	(0.19)	(0.179)	(0.27)	(0.145)	(0.51)
Lag (2months)	0.14	0.174	-0.475	-0.09	0.711	0.239	-0.157	-0.368	-0.412	-0.203	-0.189	-0.09
	(0.11)	(0.099)	(0.636)	(0.881)	(0.596)	(0.807)	(0.143)	(0.283)	(0.255)	(0.281)	(0.158)	(0.70)
Lag (4months)	-0.02	-0.121	0.692	-0.785	-0.482	-0.492	0.093	0.150	0.207	-0.0551	-0.018	0.67
	(0.08)	(0.079)	(0.467)	(0.688)	(0.454)	(0.612)	(0.098)	(0.246)	(0.181)	(0.169)	(0.112)	(0.56)
Positive	-0.06	0.065	-0.084	0.04	0.382	-0.034	0.083	-0.421	-0.175	0.414	0.0180	0.96
	(0.07)	(0.0832)	(0.492)	(0.760)	(0.452)	(0.672)	(0.098)	(0.308)	(0.137)	(0.27)	(0.143)	(0.66)
Lag (2months)	0.0007	-0.031	-0.228	0.106	-0.152	-0.611	0.0294	0.200	0.354	-0.519*	-0.0710	-1.57
	(0.09)	(0.110)	(0.602)	(1.008)	(0.605)	(0.844)	(0.119)	(0.332)	(0.196)	(0.233)	(0.147)	(0.83)
Lag (4months)	0.007	-0.083	0.216	-0.214	-0.093	0.835	-0.118	0.354	-0.253	-0.0205	-0.0006	-0.29
	(0.07)	(0.082)	(0.433)	(0.797)	(0.454)	(0.669)	(0.098)	(0.211)	(0.144)	(0.096)	(0.077)	(0.64)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.3: Heterogeneous effects: Rainfed vs Irrigated districts (Lagged versus contemporaneous Precipitation)

	Household chores		Agricultural		Non Agriculture		Casual Public		Wage/Salary		Unpaid Traineeship	
	Rain	Irrig.	Rain	Irrig.	Rain	Irrig.	Rain	Irrig.	Rain	Irrig.	Rain	Irrig.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PANEL B: MEN												
Negative	0.0585*	-0.0167	0.120	-0.678	0.0568	0.132	0.0967	-0.190	0.160	-0.158	-0.0871	0.345
	(0.0288)	(0.0432)	(0.669)	(0.733)	(0.487)	(0.608)	(0.241)	(0.248)	(0.246)	(0.350)	(0.290)	(0.456)
Lag (2months)	-0.0884	0.00235	1.270	0.448	-0.0968	0.0928	0.147	-0.0715	-0.201	0.0767	0.621	0.106
	(0.0565)	(0.0565)	(0.814)	(0.970)	(0.637)	(0.766)	(0.304)	(0.329)	(0.344)	(0.455)	(0.332)	(0.568)
Lag (4months)	0.0156	-0.00485	-1.514*	0.0147	0.281	-0.167	-0.212	0.305	0.0161	0.0780	-0.353	-0.885*
	(0.0556)	(0.0438)	(0.589)	(0.789)	(0.507)	(0.600)	(0.230)	(0.282)	(0.299)	(0.360)	(0.233)	(0.432)
Positive	-0.0443	-0.0295	-0.342	-0.752	0.263	-0.832	0.0758	0.0689	-0.126	-0.293	0.0181	-0.207
	(0.0302)	(0.0420)	(0.590)	(0.790)	(0.471)	(0.635)	(0.142)	(0.275)	(0.194)	(0.344)	(0.229)	(0.471)
Lag (2months)	0.0637	0.0426	-0.903	1.015	-0.590	0.786	-0.196	0.0845	-0.0901	-0.122	0.115	0.00759
	(0.0374)	(0.0639)	(0.764)	(1.101)	(0.623)	(0.857)	(0.180)	(0.378)	(0.284)	(0.495)	(0.286)	(0.621)
Lag (4months)	-0.0125	-0.0134	1.414*	-0.214	0.379	0.226	0.126	-0.0729	0.124	0.589	-0.290	-0.720
	(0.0287)	(0.0536)	(0.577)	(0.923)	(0.486)	(0.684)	(0.150)	(0.338)	(0.249)	(0.444)	(0.222)	(0.505)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.4: Heterogeneous effects: Rainfed vs Irrigated districts (by the severity of the shock)

	Household chores		Agricultural		Non Agriculture		Casual Public		Wage/Salary		Unpaid Traineeship	
	Rain	Irrig.	Rain	Irrig.	Rain	Irrig.	Rain	Irrig.	Rain	Irrig.	Rain	Irrig.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PANEL B: WOMEN												
$z < -3.5$	0.249	0.209	1.010	-1.632	0.222	-0.0611	0.286	0.0210	0.0472	0.0278	0.389	-1.105
	(0.366)	(0.261)	(1.464)	(2.539)	(1.161)	(1.132)	(0.522)	(0.192)	(0.400)	(0.144)	(0.662)	(1.385)
$-3.5 < z < -3$	-0.004	0.065	0.353	-0.469	-0.065	-0.001	0.0128	-0.0524	0.128	-0.258	-0.223	-0.454
	(0.142)	(0.163)	(0.621)	(1.102)	(0.516)	(0.716)	(0.170)	(0.112)	(0.191)	(0.352)	(0.139)	(0.506)
$-3 < z < -2.5$	-0.013	0.006	0.268	-0.179	0.053	0.0937	0.034	0.057	-0.027	0.0464	0.064	0.257
	(0.049)	(0.045)	(0.289)	(0.393)	(0.252)	(0.349)	(0.065)	(0.114)	(0.092)	(0.102)	(0.07)	(0.304)
$-2.5 < z < -2$	-0.021	-0.0723	0.0652	0.0297	0.216	0.0741	0.001	-0.209	-0.0408	-0.0332	-0.048	-0.893*
	(0.047)	(0.0604)	(0.304)	(0.543)	(0.296)	(0.535)	(0.0790)	(0.135)	(0.088)	(0.217)	(0.073)	(0.434)
$-2 < z < -1.5$	-0.128	0.136	0.0923	-0.271	0.280	0.166	0.0605	0.337	-0.125	0.006	-0.0002	-0.249
	(0.065)	(0.0877)	(0.359)	(0.809)	(0.453)	(0.694)	(0.149)	(0.370)	(0.112)	(0.067)	(0.099)	(0.745)
$-1.5 < z < -1$	-0.0478	-0.0756	0.0246	0.211	0.069	-0.132	-0.057	0.222	-0.0024	-0.24	-0.151	0.283
	(0.075)	(0.149)	(0.679)	(1.418)	(0.832)	(1.237)	(0.157)	(0.49)	(0.214)	(0.106)	(0.246)	(1.155)
$1 < z < 1.5$	0.012	-0.216	-0.194	-0.474	-0.280	-0.055	0.135	0.307	0.137	0.0448	-0.007	4.735
	(0.110)	(0.199)	(0.595)	(1.931)	(0.906)	(2.030)	(0.316)	(2.78)	(0.287)	(0.134)	(0.154)	(5.267)
$1.5 < z < 2$	-0.471**	-0.099	0.068	-3.118	6.392	-10.44	-0.702***	0.346	0.275***	-0.822	-0.256**	-3.726***
	(0.161)	(0.07)	(0.372)	(0.783)	(4.091)	(0.700)	(0.491)	(0.257)	(0.215)	(0.189)	(0.099)	(0.520)
$2 < z < 2.5$	-0.182**	-0.096	-0.644	-3.146	-0.119	-10.43	-0.0615***	4.359	-0.0279***	-0.817	-0.231**	-3.673***
	(0.141)	(0.07)	(0.834)	(0.786)	(1.479)	(0.703)	(0.143)	(0.257)	(0.083)	(0.191)	(0.471)	(0.522)
$z > 3$	-0.246**	-0.095	-6.496	-3.144	0.113	-0.43	-0.366***	0.362	0.643*	-0.828	-0.246*	-0.752***
	(0.323)	(0.063)	(0.079)	(0.731)	(1.618)	(0.657)	(0.104)	(0.240)	(0.327)	(0.172)	(0.105)	(0.469)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Heterogeneous effects: Rainfed vs Irrigated districts (by the severity of the shock)) II

	Household chores		Agricultural		Non Agriculture		Casual Public		Wage/Salary		Unpaid Traineeship	
	Rain	Irrig.	Rain	Irrig.	Rain	Irrig.	Rain	Irrig.	Rain	Irrig.	Rain	Irrig.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PANEL B: MEN												
$z < -3.5$	0.0345	-0.0543	0.102	0.110	0.230	0.243	0.153	-0.161	0.0172	-0.655	0.0624	-0.572
	(0.180)	(0.0376)	(1.538)	(1.400)	(1.114)	(1.381)	(0.489)	(0.261)	(0.632)	(0.370)	(0.803)	(1.569)
$-3.5 < z < -3$	-0.0195	0.0254	-0.345	-1.021	0.297	0.401	-0.0568	-0.165	-0.0914	0.111	-0.0319	-0.955
	(0.0306)	(0.0674)	(0.727)	(1.273)	(0.514)	(0.771)	(0.197)	(0.371)	(0.189)	(0.450)	(0.310)	(0.594)
$-3 < z < -2.5$	-0.00768	-0.0250	0.147	-0.187	0.190	0.0244	0.140	0.0175	0.00361	-0.0178	0.266	-0.186
	(0.0192)	(0.0258)	(0.351)	(0.408)	(0.276)	(0.332)	(0.111)	(0.171)	(0.144)	(0.188)	(0.146)	(0.255)
$-2.5 < z < -2$	0.00327	-0.0223	0.0624	-0.264	0.0828	-0.0266	-0.0424	0.0121	-0.131	0.174	-0.0865*	-0.803
	(0.0174)	(0.0308)	(0.369)	(0.593)	(0.291)	(0.432)	(0.117)	(0.240)	(0.111)	(0.366)	(0.154)	(0.352)
$-1.5 < z < -1$	-0.00195	0.0419	-0.261	-0.0146	0.0678	0.239	0.0180	0.277	-0.0476	-0.245	-0.207**	-0.993
	(0.0262)	(0.0547)	(0.466)	(0.956)	(0.441)	(0.657)	(0.150)	(0.465)	(0.182)	(0.190)	(0.191)	(0.496)
$1 < z < 1.5$	0.00594	-0.0445	0.275	0.715	0.0151	-0.827	0.004	0.0453	-0.172	-0.421	-0.112	0.309
	(0.0551)	(0.0607)	(0.765)	(1.408)	(0.722)	(1.498)	(0.224)	(1.002)	(0.124)	(0.605)	(0.300)	(1.120)
$1.5 < z < 2$	0.00102	-0.00390	-0.103	1.475	-0.0814	-0.111	0.166	-0.233	0.0553	-0.103	0.00129	-2.155*
	(0.0522)	(0.160)	(0.885)	(3.815)	(1.056)	(0.713)	(0.238)	(0.323)	(0.216)	(0.342)	(0.376)	(1.014)
$2 < z < 2.5$	-0.00906	0.0572	-0.43***	-2.674	0.73***	1.806	-0.989***	-0.429	-0.884***	1.283	-0.034***	-6.875
	(0.0344)	(0.0378)	(0.836)	(0.746)	(1.342)	(0.656)	(0.225)	(0.296)	(0.420)	(0.441)	(0.290)	(0.553)
$z > 3$	-0.00369	0.0595	-0.007***	-2.653	0.927***	1.806	-0.136***	-0.457	-0.380	1.305	0.280***	-6.718
	(0.0557)	(0.0380)	(1.403)	(0.733)	(1.543)	(0.636)	(0.153)	(0.286)	(0.205)	(0.440)	(0.817)	(0.546)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix C

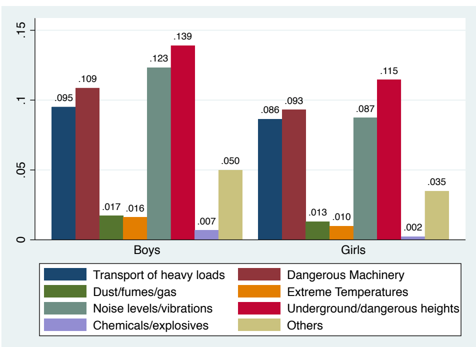
Chapter 3

C.1 Data on Hazardous Forms of Child Labour

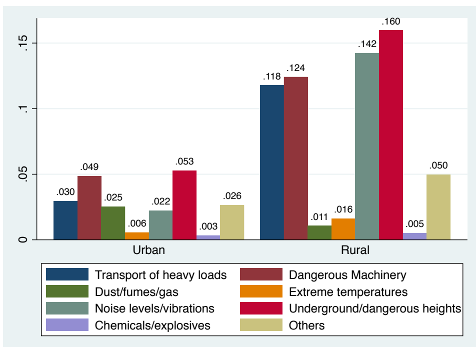
The concept of child labour varies in the academic literature, as there is no official agreed upon definition (Edmonds, 2008). While some authors use the ILO definition (Grootaert, 1998; Diallo, 2001), others employ the economic and labour intensity of the task(Ray, 2002). More and more studies use the economic activities and household chores (Guarcello et al., 2010) and the hazardous nature (Abou, 2019) to define child labour. A widely used definition of child labour is "children aged under 15 years old who engage in market activity at least one hour in a week". This being said, the term hazardous forms of child labour is defined for children under 18 years old. There is thus a difference in the age definition between that of child labour and that of hazardous forms of child labour. Following DeGraff et al. (2014) and Kamei (2018) this research examines the decision-making processes of both child labour and hazardous forms of child labour. In order to provide continuity with definitions in the child labour literature, the analytical sample focuses on children who are under the age of 15 years old.

In the child neglect module, household heads are initially asked to report whether a child is engaged in labour; they then give details on the child's working environment. Hazardous factors considered in the survey are activities that involve (i) carrying heavy loads; (ii) working with dangerous tools or operating heavy machinery; (iii) working at heights; (iv) working with or exposed to chemicals (e.g. pesticide, glues) or explosives; (v) working in dust, fumes or gas; (vi)working in extreme cold, heat or humidity, (vii) working in loud noise or vibration or (viii) working in other things, processes or conditions bad for health or safety. The ILO considers children to be involved in hazardous labour if they work in one of those hazardous factors for at least one hour during a reference week.

In Table C.1, column (1) shows that 27 per cent of children are engaged in economic activity (child labour) at least 1 hour in the reference week. Children work on average 7 hours a week. While there is a generally recognized consensus that census data underestimate child labour, particularly in hazardous forms of child labour, 20% of children are reported to be working in hazardous environments. These children work for around 30 hours a week (column 4), compared to 22 hours for children involved in non-hazardous jobs (column 3). Figure **??** presents the rate of hazardous factors among working children, (a) compares the data by gender, while (b) shows an urban and rural comparison. The data show that for boys and girls, 14 per cent and 12 per cent, respectively report that their work involved being underground or at dangerous heights, the next most prevalent hazardous factor involves being exposed to high noise levels or vibrations and operating dangerous machinery. Other hazardous factors are less than 10 per cent for each.



(a)



(b)

Table C.1: Descriptive Statistics by work status

					MEAN DIFF		
	Total (1)	No work (2)	Non-Hazardous (3)	Hazardous (4)	(3) vs (2) (5)	(4) vs (2) (6)	Min-Max (7)
Child Labour	0.27 (0.44)						0-1
Hazardous	0.20 (0.40)						0-1
Hours of work (week)	7.47 (19.06)		21.51 (25.98)	29.70 (28.47)	-0.71 (0.16)***	-29.70 (0.53)***	0-99
Enrolled	0.73 (0.44)	0.75 (0.43)	0.72 (0.45)	0.64 (0.48)	0.04 (0.01)**	0.12 (0.01)***	0-1
Wealth Index	2.78 (1.35)	2.60 (1.32)	2.47 (1.21)	2.02 (1.01)	0.13(0.04)***	0.58 (0.02)***	1-5
Female	0.49 (0.50)	0.50 (0.50)	0.51 (0.50)	0.45 (0.50)	-0.01 (0.02)	0.05 (0.01)***	0-1
Age	9.66 (2.57)	9.54 (2.56)	9.93 (2.82)	9.98 (2.53)	-0.39 (0.08)***	-0.44 (0.05)***	6-14
Rural	0.69 (0.46)	0.68 (0.48)	0.75 (0.43)	0.88 (0.33)	-0.11 (0.01)***	-0.24 (0.01)***	0-1
Household size	7.97 (3.98)	7.87 (3.90)	8.58 (4.99)	8.10 (3.81)	-0.71(0.16)***	-0.23 (0.08)**	2-45
<5years (#)	1.51 (1.37)	1.55 (1.35)	1.40 (1.42)	1.43 (1.39)	0.14 (0.05)**	0.12 (0.03)***	0-9
6-14 years (#)	3.17 (1.89)	3.07 (1.82)	3.68 (2.56)	3.37 (1.79)	-0.61 (0.08)***	-0.30 (0.04)***	1-16
>60years (#)	0.33 (0.64)	0.32 (0.63)	0.38 (0.68)	0.35 (0.65)	-0.06 (0.02)**	-0.04 (0.01)**	0-5
Head(female)	0.16 (0.37)	0.17 (0.37)	0.11 (0.32)	0.16 (0.36)	0.05 (0.01)***	0.01 (0.00)	0-1
Head(age)	48.65 (12.91)	48.10 (12.92)	50.69 (13.30)	49.90 (12.56)	-2.58 (0.43)***	-1.80 (0.27)***	17-99
Agricultural Land	8.23 (18.86)	7.43 (17.83)	9.04 (20.83)	10.86 (21.36)	-1.61 (0.66)**	-3.43 (0.44)***	0-99
Livestock	2.17 (10.68)	1.99 (10.71)	3.08 (13.71)	2.53 (9.17)	-1.09 (0.43)**	-0.54 (0.20)**	0-99
Horse/Donkey	0.15 (3.47)	0.19 (4.06)	0.08 (0.60)	0.02 (0.21)	0.11 (0.04)**	0.17 (0.04)***	0-99
Chicken	6.87(14.96)	5.97 (13.82)	9.90 (16.47)	9.03 (17.75)	-3.92 (0.52)***	-3.05 (0.36)***	0-99
Has electricity	0.55 (0.50)	0.59 (0.49)	0.54 (0.50)	0.40 (0.49)	0.05 (0.02)***	0.19 (0.01)***	0-1
Has access to water	0.16 (0.36)	0.19 (0.39)	0.09 (0.29)	0.05 (0.23)	0.10 (0.01)***	0.13 (0.01)***	0-1
Independent child	0.19 (0.39)	0.19 (0.39)	0.18 (0.39)	0.20 (0.40)	0.01 (0.00)	-0.01 (0.00)***	0-1
Father away	0.02 (0.13)	0.01 (0.12)	0.02 (0.14)	0.02 (0.14)	-0.01 (0.00)	-0.01 (0.00)*	0-1
Father dead	0.07 (0.25)	0.07 (0.25)	0.07 (0.25)	0.06 (0.24)	-0.00 (0.00)	0.01 (0.00)	0-1
Mother away	0.28 (0.45)	0.26 (0.45)	0.29 (0.45)	0.30 (0.44)	-0.03 (0.01)	-0.04 (0.08)*	0-1
Mother dead	0.04 (0.19)	0.04 (0.20)	0.04 (0.19)	0.04 (0.19)	-0.00 (0.00)	-0.00 (0.00)	0-1
N	14347	10447	1060	2840			

Table C.2: Data Description for Selected Variables

Variables	Description
Household Characteristics	
Household size (#)	Total number of household members
Head (Female)	1 if the head is a female, 0 otherwise
Head (Age)	Age of the head of household in years
Rural	1 if the household lives in a rural area, 0 otherwise
<5 years old (#)	Number of individual aged 0-4 in the household
6-14 years old (#)	Number of individual aged 6-14 in the household
>60 years old (#)	Number of individual aged 60 and above in the household
Male (#)	Number of males in the household
Wealth index index	Asset based wealth calculated using https://dhsprogram.com/topics/wealth-index/Wealth-Index-Construction.cfm
Household assets	
Agricultural land	Hectares of agricultural land owned by the household
Livestock (#)	Number of livestock owned by the household
Horse/donkey	Number of Horse/donkey owned by the household
Chicken	Number of Chicken owned by the household
Has electrictity	1 if the household has electricity, 0 otherwise
Has access to water	1 if the household has access to drinking water, 0 otherwise
Child characteristics	
Child labour	1 if the child participates in economic activity at least 1 hour in a reference week, 0 otherwise
Hazardous child labour	1 if the child is exposed to any of the hazardous factors at their working site, otherwise 0
Hours of work	Number of hours of work in economic activity
Enrolled school	1 if the child is enrolled in school in the year of survey, otherwise 0
Female	1 if the child is female, 0 otherwise
Age	Age of the child in years
Independent child	1 if both biological parents are absent in the household, otherwise 0
Father away	1 if biological father is still alive but absent in the household, otherwise 0
Father dead	1 if biological father is dead, otherwise 0
Mother away	1 if biological mother is still alive but absent in the household, otherwise 0
Mother dead	1 if biological mother is dead, otherwise 0
Violence Against Children	
Emotional Abuse	1 if the caregiver Screamed, shouted at him/her and/or called him/her stupid, lazy or another name, otherwise 0
Mild Physical Abuse	1 if the caregiver shook him/her. and/or Spanked, hit or slapped him/her on the bottom with bare hand hit and/or slapped him/her on the hand, arm or leg?, otherwise 0
Extreme Physical Abuse	1 if the caregiver hit or slapped him/her on the face, head or ears and/or hit him/her on the bottom or elsewhere on the body with a hard object like a belt and/or beat him/her up with a device (repeatedly hit as hard as possible), otherwise 0
Region (31 geographical regions)	
Agnéby-Tiassa, Bafing, Bagoué, Bélier Region, Béré, Bounkani, Cavally, Folon, Gbêkê, Gbôklé, Gôh, Gontougo, Grands-Ponts, Guémon, Hambol, Haut-Sassandra, Iffou, Indénié-Djuablin, Kabadougou, La Mé, Lôh-Djiboua, Marahoué, Moronou, Nawa, N'Zi, Poro, San-Pédro, Sud-Comoé, Tchologo, Tonkpi, Worodougou	

C.1.1 Data Description for Selected Variables

C.1.2 Descriptive Statistics by the different types of abuse

C.2 Methodology: Hazardous child forms of child labour

To examine the determinants of hazardous child forms of child labour I follow Kamei (2018), who employs a two-stage decision process in which households

Table C.3: Descriptive Statistics by the different types of abuse

	Total	No Abuse	Emotional Abuse	Mild Physical Abuse	Extreme Physical Abuse	MEAN DIFF (3) vs (2)	MEAN DIFF (4) vs (2)	MEAN DIFF (5) vs (2)	Min-Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Emotional Abuse	0.77 (0.42)								0-1
Mild Physical Abuse	0.57 (0.50)								0-1
Extreme Physical Abuse	0.24 (0.43)								0-1
Enrolled	0.73 (0.44)	0.74 (0.44)	0.72 (0.45)	0.71 (0.45)	0.68 (0.46)	0.02 (0.01)	0.03 (0.01)**	0.05 (0.01)***	0-1
Wealth Index	2.78 (1.35)	2.83 (1.34)	2.53 (1.30)	2.52 (1.30)	2.45 (1.28)	0.29 (0.03)***	0.30 (0.03)***	0.37 (0.03)***	1-5
Female	0.49 (0.50)	0.49 (0.50)	0.49 (0.50)	0.48 (0.50)	0.46 (0.50)	0.00 (0.01)	0.01 (0.01)	0.03 (0.01)**	0-1
Age	9.66 (2.57)	9.89 (2.63)	9.60 (2.55)	9.44 (2.53)	9.45 (2.51)	(0.29) (0.05)***	0.45 (0.06)***	0.44 (0.06)***	6-14
Rural	0.69 (0.46)	0.64 (0.48)	0.71 (0.45)	0.71 (0.45)	0.73 (0.44)	-0.08 (0.01)***	-0.07 (0.01)***	-0.09 (0.01)***	0-1
Household size	7.97 (3.98)	8.49 (4.64)	7.82 (3.77)	7.89 (3.70)	7.79 (3.43)	0.66 (0.08)***	0.60 (0.09)***	0.70 (0.10)***	2-45
<5 years (#)	1.51 (1.37)	1.46 (1.41)	1.52 (1.35)	1.61 (1.35)	1.57 (1.38)	1.50 (0.01)**	-0.15 (0.03)***	-0.12 (0.04)***	0-8
6-14 years (#)	3.17 (1.89)	3.17 (2.12)	3.18 (1.82)	3.17 (1.83)	3.13 (1.74)	-0.01 (0.04)	0.00 (0.04)	0.04 (0.05)	1-11
>60years (#)	0.33 (0.64)	0.35 (0.66)	0.33 (0.63)	0.31 (0.63)	0.31 (0.63)	0.02 (0.01)	0.04 (0.01)**	0.04 (0.02)**	0-5
Head (Female)	0.16 (0.37)	0.15 (0.35)	0.17 (0.37)	0.17(0.37)	0.19 (0.39)	-0.02 (0.01)**	-0.02 (0.01)**	-0.04 (0.01)***	0-1
Head (age)	48.65 (12.91)	49.60 (13.48)	48.49 (12.79)	48.00 (12.72)	48.26 (12.98)	1.11 (0.27)***	1.59 (0.30)***	1.34 (0.33)***	17-98
Land(hectares)	8.23 (18.86)	7.89 (17.42)	8.32 (19.25)	8.10 (18.72)	8.20 (18.59)	-0.43 (0.39)	-0.21 (0.39)	-0.32 (0.46)	0-99
Livestock	2.17 (10.68)	2.62 (12.43)	2.02 (9.97)	2.03 (10.05)	1.68 (8.54)	0.60 (0.22)**	0.58 (0.23)**	0.93 (0.27)***	0-99
Horse/Donkey	0.15 (3.47)	0.11 (2.38)	0.15 (3.53)	0.19 (4.09)	0.15 (3.53)	-0.04 (0.07)	-0.08 (0.08)	-0.04 (0.08)	0-99
Chicken	6.87(14.96)	6.39 (13.76)	6.95 (15.03)	7.06 (15.13)	6.52 (13.65)	-0.55 (0.31)	-0.67 (0.31)**	-0.13 (0.35)	0-99
Has electricity	0.55 (0.50)	0.61 (0.49)	0.53 (0.50)	0.53 (0.50)	0.51 (0.50)	0.08 (0.01)***	0.08 (0.01)***	0.10 (0.01)***	0-1
Has access to water	0.16 (0.36)	0.19 (0.39)	0.15 (0.35)	0.15 (0.35)	0.14 (0.35)	0.04 (0.01)***	0.04 (0.01)***	0.05 (0.01)***	0-1
Independent child	0.19 (0.39)	0.21 (0.41)	0.19 (0.39)	0.18 (0.38)	0.18 (0.38)	0.02 (0.01)***	0.04 (0.01)***	0.03 (0.01)***	0-1
Father away	0.02 (0.13)	0.02 (0.14)	0.02 (0.13)	0.02 (0.13)	0.01 (0.12)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0-1
Father dead	0.07 (0.25)	0.06 (0.24)	0.06 (0.24)	0.07 (0.25)	0.07 (0.25)	0.00 (0.00)	-0.01 (0.00)	-0.01 (0.01)	0-1
Mother away	0.28 (0.45)	0.27 (0.44)	0.28 (0.45)	0.26 (0.44)	0.30 (0.46)	-0.01 (0.01)*	0.01 (0.04)***	-0.03 (0.01)**	0-1
Mother dead	0.04 (0.19)	0.03 (0.16)	0.04 (0.19)	0.03 (0.17)	0.05 (0.21)	-0.01 (0.00)**	-0.00 (0.00)***	-0.02 (0.00)***	0-1
N	14347	2944	11003	8196	3377				

first decide whether to send children to work or not. Thereafter, if they send the children to work, they choose between two types of children's working environment. The first is an environment with hazardous conditions, and the second is a non-hazardous work. Figure C.1 presents the sequential logit model. Therefore, the results from the second stage indicate the probability of choosing hazardous forms of child labour, given that the child is working.

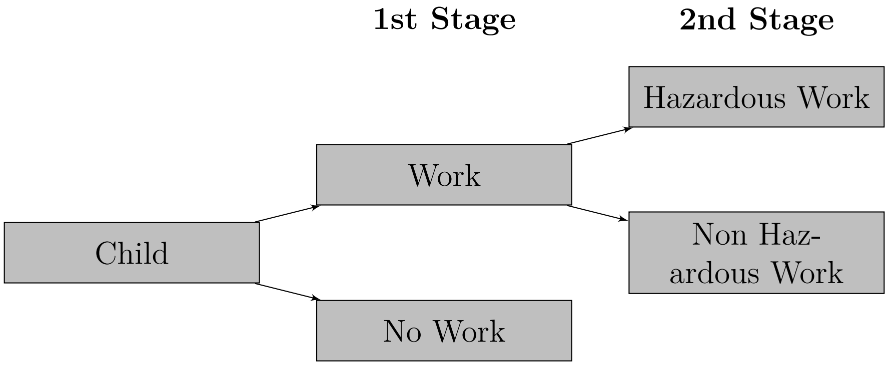


Figure C.1: Sequential logit model for hazardous child labour, (Kamei, 2018)

C.2.1 Additional Results

Table C.4: Logit Regression Analysis on Child Abuse

	Child abuse					
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0855***	0.0745***	0.0119**	0.0106**	0.0104**	0.0104***
	(0.0449)	(0.0424)	(0.0424)	(0.0423)	(0.0420)	(0.0419)
Rural	0.219***	0.0995***	0.0662***	0.0524***	0.0521***	0.0515***
	(0.0569)	(0.0623)	(0.0630)	(0.0636)	(0.0636)	(0.0636)
Household size	0.0386***	0.0362***	0.150***	0.154***	0.154***	0.154***
	(0.00483)	(0.00490)	(0.0106)	(0.0107)	(0.0107)	(0.0107)
Independent	0.145***	0.147***	0.160***	0.155**	0.161**	0.167*
	(0.0813)	(0.0813)	(0.0826)	(0.0827)	(0.0828)	(0.0843)
Father away	0.0245	0.0365	0.0180	0.00879	0.0123	-0.189
	(0.162)	(0.162)	(0.163)	(0.163)	(0.163)	(0.251)
Father dead	0.0535	0.0474	0.0574	0.0847	0.0565	-0.0210
	(0.0891)	(0.0891)	(0.0895)	(0.0920)	(0.0922)	(0.124)
Mother away	-0.0141	0.00725	0.0171	0.00848	0.0141	0.0208
	(0.0715)	(0.0716)	(0.0726)	(0.0728)	(0.0729)	(0.0742)
Mother dead	0.233*	0.219*	0.192*	0.153*	0.196*	0.1086*
	(0.104)	(0.104)	(0.106)	(0.111)	(0.112)	(0.152)
Has electricity	-0.152**	0.0258	0.00673	0.0141	0.0143	0.0143
	(0.0504)	(0.0621)	(0.0626)	(0.0625)	(0.0625)	(0.0626)
Has water	-0.0937	0.0338	0.0632	0.0726	0.0709	0.0709
	(0.0656)	(0.0704)	(0.0712)	(0.0715)	(0.0716)	(0.0716)
Wealth Index		-0.149***	-0.124***	-0.122***	-0.122***	-0.122***
		(0.0300)	(0.0303)	(0.0303)	(0.0303)	(0.0303)
<5years			0.210***	0.213***	0.213***	0.213***
			(0.0221)	(0.0223)	(0.0222)	(0.0223)
6-14 years			0.203***	0.204***	0.204***	0.204***
			(0.0197)	(0.0197)	(0.0197)	(0.0197)
>60years			0.0697*	0.0771*	0.0731*	0.0731*
			(0.0369)	(0.0371)	(0.0370)	(0.0370)
Land(hectares)				0.00189	0.00188	0.00185
				(0.00116)	(0.00116)	(0.00116)
(#) Livestock				-0.00449	-0.00453	-0.00459
				(0.00212)	(0.00211)	(0.00212)
(#) Horse & Donkey				0.00969	0.00977	0.00931
				(0.00686)	(0.00684)	(0.00689)
(#) Chicken				0.00369	0.00367	0.00369
				(0.00154)	(0.00153)	(0.00153)
Independent Child × Grandparents					-0.0220	
					(0.332)	
Independent Child × Female						-0.0799
						(0.345)
Father away × Female						0.286
						(0.338)
Father dead × Female						0.164
						(0.183)
Mother away × Female						0.124
						(0.247)
Mother dead × Female						-0.167
						(0.227)
N	14347	14347	14347	14347	14347	14347

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.5: Logit Regression Analysis on Child Abuse by the type of Abuse

	Emotional Abuse		Mild Physical Abuse		Extreme Physical Abuse	
	(1)	(2)	(1)	(2)	(1)	(2)
Female	0.0141***	0.0135***	0.0563	0.0066	0.0136***	0.0155***
	(0.0404)	(0.0428)	(0.0347)	(0.0368)	(0.0401)	(0.0423)
Rural	0.0402**	0.0386**	0.053**	0.0533**	0.0633***	0.0631***
	(0.0609)	(0.0609)	(0.0525)	(0.0525)	(0.0626)	(0.0627)
Household size	0.133***	0.133***	0.0879***	0.0881	0.0366***	0.0370***
	(0.0104)	(0.0104)	(0.00871)	(0.00871)	(0.00966)	(0.00967)
Independent	0.140**	0.147**	0.291***	0.296***	0.0616***	0.0626***
	(0.0798)	(0.0814)	(0.0682)	(0.0690)	(0.0808)	(0.0819)
Father away	0.0512	-0.0740	-0.0590	-0.304	-0.198	-0.574*
	(0.158)	(0.244)	(0.132)	(0.215)	(0.171)	(0.295)
Father dead	0.0322	-0.0609	-0.107	-0.0772	-0.0383	-0.271
	(0.0884)	(0.119)	(0.0735)	(0.100)	(0.0892)	(0.126)
Has electricity	0.0384	0.0384	0.0748	0.0725	0.0573	0.0516
	(0.0599)	(0.0600)	(0.0509)	(0.0510)	(0.0575)	(0.0575)
Has water	-0.138*	-0.137*	0.107	0.105	0.0543	0.0514
	(0.0684)	(0.0684)	(0.0598)	(0.0598)	(0.0720)	(0.0720)
Wealth Index	-0.159***	-0.159***	-0.122***	-0.121***	-0.116***	-0.115***
	(0.0289)	(0.0289)	(0.0247)	(0.0247)	(0.0280)	(0.0280)
<5years	0.156***	0.155***	0.229***	0.228***	0.0860***	0.0844***
	(0.0212)	(0.0213)	(0.0178)	(0.0178)	(0.0199)	(0.0199)
6-14years	0.183***	0.183***	0.0922***	0.0925***	0.0309***	0.0312***
	(0.0188)	(0.0188)	(0.0150)	(0.0150)	(0.0165)	(0.0165)
>60years	0.0908*	0.0928**	0.0123	0.0145	0.00115	0.00464
	(0.0360)	(0.0360)	(0.0291)	(0.0290)	(0.0341)	(0.0341)
Land(hectares)	0.00191	0.00188	-0.000926	-0.000913	-0.000279	-0.000313
	(0.00111)	(0.00111)	(0.000938)	(0.000938)	(0.00110)	(0.00110)
(#) Livestock	-0.00218	-0.00239	-0.00451	-0.00449	-0.00453	-0.00459
	(0.00200)	(0.00200)	(0.00181)	(0.00181)	(0.00248)	(0.00247)
(#) Horse & Donkey	0.000936	0.000488	0.0108	0.0108	0.00419	0.00434
	(0.00596)	(0.00595)	(0.00586)	(0.00587)	(0.00600)	(0.00602)
(#) Chicken	0.00117	0.00118	0.00165	0.00165	-0.00402	-0.00397
	(0.00141)	(0.00141)	(0.00126)	(0.00126)	(0.00154)	(0.00153)
Independent Child × Grandparents	-0.724		-0.976		-1.005	
	(0.320)		(0.289)		(0.462)	
Independent Child × Female		-0.0489		-0.0226		-0.686
		(0.337)		(0.294)		(0.446)
Father away × Female		0.135		0.501		0.738
		(0.324)		(0.277)		(0.365)
Father dead × Female		0.192		-0.00659		0.509
		(0.175)		(0.144)		(0.172)
Mother away × Female		0.188		-0.249		-0.367
		(0.235)		(0.187)		(0.238)
Mother dead × Female		-0.205		-0.320		-0.339
		(0.219)		(0.194)		(0.257)
N	14347	14347	14347	14347	14347	14347

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.6: Robustness Checks: LPM Regression Analysis on Child Abuse

	Child Abuse					
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0770***	0.0652***	0.0190***	0.0163***	0.0160***	0.0224***
	(0.0673)	(0.0673)	(0.0668)	(0.0657)	(0.0638)	(0.00635)
Rural	0.374***	0.0176***	0.0132***	0.0310***	0.0409***	0.0608***
	(0.173)	(0.0156)	(0.0154)	(0.0176)	(0.0187)	(0.0207)
Household size	0.0676***	0.0632***	0.252***	0.256***	0.256***	0.256***
	(0.0910)	(0.0092)	(0.0171)	(0.0173)	(0.0173)	(0.0173)
Independent	0.0242**	0.0246**	0.0259**	0.0249**	0.0258**	0.0268*
	(0.0133)	(0.0133)	(0.0133)	(0.0133)	(0.0133)	(0.0135)
Father away	0.00389	0.00595	0.00352	0.00188	0.00246	-0.0319
	(0.0271)	(0.0271)	(0.0269)	(0.0269)	(0.0269)	(0.0456)
Father dead	0.00774	0.00695	0.00934	0.0137	0.00947	-0.00376
	(0.0143)	(0.0143)	(0.0142)	(0.0144)	(0.0145)	(0.0202)
Mother away	-0.00245	0.000883	0.00248	0.00112	0.00197	0.00301
	(0.0114)	(0.0114)	(0.0114)	(0.0114)	(0.0114)	(0.0116)
Mother dead	-0.0398*	-0.0376*	-0.0328	-0.0259	-0.0333	-0.0164
	(0.0189)	(0.0189)	(0.0189)	(0.0194)	(0.0198)	(0.0262)
Electricity	-0.0228**	0.00543	0.00322	0.00455	0.00458	0.00459
	(0.00791)	(0.00966)	(0.00960)	(0.00961)	(0.00961)	(0.00962)
Has water	-0.0168	0.00412	0.00826	0.00971	0.00946	0.00948
	(0.0117)	(0.0126)	(0.0124)	(0.0125)	(0.0125)	(0.0125)
Wealth Index		-0.0241***	-0.0202***	-0.0201***	-0.0201***	-0.0201***
		(0.00492)	(0.00491)	(0.00491)	(0.00491)	(0.00491)
<5years			0.0336***	0.0340***	0.0340***	0.0340***
			(0.00329)	(0.00329)	(0.00329)	(0.00329)
6-14years			0.0324***	0.0324***	0.0325***	0.0325***
			(0.00289)	(0.00288)	(0.00288)	(0.00288)
>60years			0.00911	0.0100	0.00944	0.00946
			(0.00567)	(0.00567)	(0.00567)	(0.00567)
Land(hectares)				0.000283	0.000282	0.000278
				(0.00017)	(0.00017)	(0.00017)
Livestock				-0.000737	-0.000743	-0.000753
				(0.000397)	(0.000396)	(0.000396)
(#) Horse_donkey				0.00158	0.00159	0.00152
				(0.000889)	(0.000884)	(0.000894)
(#) Chicken				0.000560*	0.000557*	0.000559*
				(0.000228)	(0.000228)	(0.000228)
Independent Child × Grandparents					-0.113	
					(0.0604)	
Independent Child × Female						-0.0119
						(0.0624)
Father away × Female						0.0484
						(0.0571)
Father dead × Female						0.0272
						(0.0284)
Mother away × Female						0.0183
						(0.0353)
Mother dead × Female						-0.0303
						(0.0407)
N	14347	14347	14347	14347	14347	14347

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.7: Robustness Checks: LPM Regression Analysis on Child Abuse by type

	Emotional Abuse		Mild Physical Abuse		Extreme Physical Abuse	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.00225	0.00484	0.0136	0.0141	0.0237***	0.0290***
	(0.00700)	(0.00739)	(0.00816)	(0.00864)	(0.00705)	(0.00751)
Rural	0.839	0.00811*	0.0119	0.0115	0.0487**	0.0101**
	(0.111)	(0.0111)	(0.0125)	(0.0125)	(0.0104)	(0.0104)
Household size	0.0241***	0.0240***	0.0205***	0.0206***	0.00595***	0.00601***
	(0.00181)	(0.00181)	(0.00195)	(0.00195)	(0.00157)	(0.00157)
Independent	0.0389**	0.0420**	0.0243**	0.0212**	0.0116**	0.0334**
	(0.0138)	(0.0139)	(0.0164)	(0.0166)	(0.0138)	(0.0140)
Mother away	0.0144	0.0174	-0.0299	-0.0323	-0.00155	-0.00475
	(0.0118)	(0.0119)	(0.0142)	(0.0144)	(0.0121)	(0.0123)
Mother dead	-0.0250	-0.0263	-0.0838***	-0.105***	-0.0559**	-0.0508*
	(0.0201)	(0.0276)	(0.0225)	(0.0304)	(0.0173)	(0.0238)
Father away	0.0169	-0.00456	-0.0237	-0.0805	-0.0289	-0.0857
	(0.0279)	(0.0460)	(0.0316)	(0.0518)	(0.0255)	(0.0371)
Father dead	0.00724	-0.0129	-0.00106	0.00218	-0.00261	-0.0385
	(0.0152)	(0.0213)	(0.0175)	(0.0239)	(0.0149)	(0.0199)
Has electricity	0.00863	0.00881	0.0171	0.0165	0.00893	0.00793
	(0.0101)	(0.0101)	(0.0120)	(0.0120)	(0.0103)	(0.0103)
Has water	0.0231	0.0229	0.0250	0.0245	0.00974	0.00981
	(0.0129)	(0.0129)	(0.0143)	(0.0143)	(0.0117)	(0.0117)
Wealth Index	-0.0285***	-0.0286***	-0.0280***	-0.0277***	-0.0196***	-0.0193***
	(0.00513)	(0.00513)	(0.00582)	(0.00582)	(0.00477)	(0.00477)
<5years	0.0274***	0.0274***	0.0522***	0.0522***	0.0146***	0.0144***
	(0.00350)	(0.00350)	(0.00393)	(0.00393)	(0.00353)	(0.00353)
6-14 years	0.0318***	0.0318***	0.0213***	0.0215***	0.00490	0.00498
	(0.00305)	(0.00305)	(0.00340)	(0.00340)	(0.00285)	(0.00285)
>60years	0.0152*	0.0146*	0.00486	0.00402	0.00162	0.00122
	(0.00592)	(0.00592)	(0.00681)	(0.00679)	(0.00590)	(0.00586)
Land (hectares)	0.000315	0.000307	-0.000214	-0.000212	-0.0000458	-0.0000540
	(0.000179)	(0.000179)	(0.000222)	(0.000222)	(0.000191)	(0.000191)
(#) Horse & donkey	0.000295	0.000220	0.00239*	0.00246*	0.000771	0.000792
	(0.00101)	(0.00101)	(0.000972)	(0.000967)	(0.000990)	(0.000990)
(#)Chicken	0.000199	0.000195	0.000388	0.000387	-0.000660**	-0.000652**
	(0.000239)	(0.000239)	(0.000284)	(0.000284)	(0.000239)	(0.000239)
Independent Child × Grandparents	-0.116		-0.165*		-0.0816	
	(0.0792)		(0.0743)		(0.0512)	
Independent Child × Female		-0.000762		-0.0164		-0.0949
		(0.0641)		(0.0706)		(0.0511)
Father away × Female		0.0211		0.119		0.112*
		(0.0584)		(0.0659)		(0.0509)
Father dead × Female		0.0298		-0.0125		0.0816**
		(0.0300)		(0.0344)		(0.0294)
Mother away × Female		0.0396		-0.0756		-0.0595
		(0.0361)		(0.0450)		(0.0340)
Mother dead × Female		-0.0104		0.0239		-0.000143
		(0.0421)		(0.0465)		(0.0358)
N	14347	14347	14347	14347	14347	14347

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.8: Logit Regression Analysis on Child Abuse by the type of Abuse: Emotional and Physical Child Abuse

	Emotional Abuse						Mild Physical Abuse						Extreme Physical Abuse					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0143	0.0136	0.0157	0.0142	0.0141	0.0235	0.0475	0.0468	0.0554	0.0564	0.0563	0.0466	0.131**	0.131**	0.134***	0.136***	0.136***	0.155***
	(0.36)	(0.34)	(0.39)	(0.35)	(0.35)	(0.55)	(1.39)	(1.36)	(1.60)	(1.63)	(1.63)	(1.27)	(3.27)	(3.27)	(3.34)	(3.38)	(3.39)	(3.69)
Rural	0.225***	0.0823***	0.0544**	0.0400**	0.0402**	0.0386**	0.0833**	0.0321**	0.0542**	0.0531***	0.053**	0.0533**	0.157**	0.0547**	0.0465***	0.0636***	0.0633***	0.0631***
	(4.11)	(1.38)	(0.90)	(0.66)	(0.66)	(0.63)	(1.75)	(0.62)	(1.04)	(1.01)	(1.01)	(1.01)	(2.72)	(0.88)	(0.75)	(1.02)	(1.01)	(1.01)
Household size	0.0360***	0.0331***	0.131***	0.133***	0.133***	0.133***	0.00899*	0.00644	0.0865***	0.0879***	0.0879***	0.0881***	0.0119*?	0.00934	0.0399***	0.0365***	0.0366***	0.0370***
	(7.68)	(7.00)	(12.80)	(12.83)	(12.83)	(12.82)	(2.07)	(1.47)	(9.99)	(10.09)	(10.10)	10.12)	(2.34)	(1.84)	(4.16)	(3.78)	(3.78)	(3.83)
Independent	0.115**	0.117*	0.140**	0.140**	0.140**	0.147**	0.233***	0.230***	0.291***	0.293***	0.291***	0.296***	0.0875***	0.0769***	0.0588***	0.0623***	0.0616***	0.0626***
	(2.25)	(2.28)	(2.64)	(2.68)	(2.69)	(2.77)	(5.51)	(5.18)	(4.18)	(4.22)	(4.18)	(4.27)	(1.65)	(1.45)	(1.07)	(1.14)	(1.11)	(1.13)
Father away	0.0660	0.0702	0.0493	0.0518	0.0512	-0.0740	-0.0425	-0.0383	-0.0440	-0.0583	-0.0590	-0.304	-0.199	-0.195	-0.198	-0.197	-0.198	-0.574*
	(0.43)	(0.46)	(0.32)	(0.34)	(0.33)	(-0.31)	(-0.33)	(-0.30)	(-0.34)	(-0.45)	(-0.46)	(-1.41)	(-1.19)	(-1.17)	(-1.19)	(-1.18)	(-1.18)	(-1.96)
Father dead	0.0128	0.0143	0.0176	0.0553	0.0322	-0.0609	-0.145	-0.143	-0.105	-0.0634	-0.107	-0.0772	-0.0888	-0.0868	-0.0688	-0.0410	-0.0383	-0.271
	(0.15)	(0.17)	(0.21)	(0.64)	(0.37)	(-0.53)	(-2.10)	(-2.07)	(-1.52)	(-0.90)	(-1.50)	(-0.79)	(-1.05)	(-1.03)	(-0.81)	(-0.48)	(-0.44)	(-2.20)
Has electricity	-0.161***	0.0507	0.0344	0.0382	0.0384	0.0384	-0.0886*	0.0778	0.0714	0.0741	0.0748	0.0725	-0.0724	0.0705	0.0689	0.0569	0.0573	0.0516
	(-3.35)	(0.85)	(0.57)	(0.64)	(0.64)	(0.64)	(-2.16)	(1.54)	(1.40)	(1.45)	(1.47)	(1.42)	(-1.50)	(1.23)	(1.20)	(0.99)	(1.00)	(0.90)
Has water	-0.0436	0.108	0.131	-0.139*	-0.138*	-0.137*	-0.0462	0.0769	0.103	0.109	0.107	0.105	-0.0608	0.0470	0.0560	0.0528	0.0543	0.0514
	(-0.69)	(1.60)	(1.92)	(-2.03)	(-2.02)	(-2.01)	(-0.84)	(1.30)	(1.73)	(1.82)	(1.79)	(1.76)	(-0.91)	(0.65)	(0.78)	(0.73)	(0.75)	(0.71)
Wealth Index		-0.178***	-0.157***	-0.159***	-0.159***	-0.159***		-0.141***	-0.122***	-0.122***	-0.122***	-0.121***		-0.123***	-0.117***	-0.116***	-0.116***	-0.115***
		(-6.21)	(-5.45)	(-5.52)	(-5.51)	(-5.50)		(-5.82)	(-4.97)	(-4.95)	(-4.94)	(-4.90)		(-4.47)	(-4.20)	(-4.18)	(-4.16)	(-4.11)
<5years			0.154***	0.156***	0.156***	0.155***			0.228***	0.228***	0.229***	0.228***			0.0888***	0.0856***	0.0860***	0.0844***
			(7.31)	(7.35)	(7.37)	(7.32)			(12.83)	(12.83)	(12.87)	(12.83)			(4.48)	(4.31)	(4.33)	(4.25)
6-14years			0.183***	0.183***	0.183***	0.183***			0.0917***	0.0915***	0.0922***	0.0925***			0.0308***	0.0303***	0.0309***	0.0312***
			(9.75)	(9.68)	(9.71)	(9.69)			(6.12)	(6.10)	(6.15)	(6.17)			(1.88)	(1.85)	(1.88)	(1.90)
>60years			0.0903*	0.0964**	0.0908*	0.0928**			0.0117	0.0179	0.0123	0.0145			0.00333	0.00632	0.00115	0.00464
			(2.51)	(2.67)	(2.53)	(2.58)			(0.40)	(0.61)	(0.42)	(0.50)			(0.10)	(0.18)	(0.03)	(0.14)
Land(hectares)				0.00193	0.00191	0.00188				-0.000926	-0.000926	-0.000913				-0.000268	-0.000279	-0.000313
				(1.75)	(1.73)	(1.71)				(-0.99)	(-0.99)	(-0.98)				(-0.24)	(-0.25)	(-0.28)
(#) Horse & Donkey				0.000920	0.000936	0.000488				0.0107	0.0108	0.0108				0.00419	0.00419	0.00434
				(0.16)	(0.17)	(0.09)				(1.93)	(1.93)	(1.93)				(0.76)	(0.76)	(0.79)
(#) Chicken				0.00120	0.00117	0.00118				0.00167	0.00165	0.00165				-0.00400	-0.00402	-0.00397
				(0.86)	(0.84)	(0.85)				(1.36)	(1.34)	(1.35)				(-2.64)	(-2.65)	(-2.62)
Independent Child × Grandparents					-0.724						-0.976						-1.005	
					(-2.11)						(-2.83)						(-1.90)	
Independent Child × Female						-0.0489						-0.0226						-0.686
						(-0.15)						(-0.08)						(-1.54)
Father away × Female						0.135						0.501						0.738
						(0.42)						(1.81)						(2.03)
Father dead × Female						0.192						-0.00659						0.509
						(1.11)						(-0.05)						(2.97)
Mother away × Female						0.188						-0.249						-0.367
						(0.82)						(-1.35)						(-1.56)
Mother dead × Female						-0.205						-0.320						-0.339
						(-1.25)						(-2.17)						(-1.70)
N	14347	14347	14347	14347	14347	14347	14347	14347	14347	14347	14347	14347	14347	14347	14347	14347	14347	14347

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.3 Robustness checks

Table C.11 presents the estimation results from a Linear Probability Model on child neglect, that is child labour and its hazardous forms. While the first stage estimation is OLS regression on child labour using the whole sample, the second stage estimates OLS regression on hazardous child labour, with the sample restricted to working children. All coefficients show a similar trend with the main analysis. However, the number of hectares of land owned by the household is no longer statistically significant, and even though the effect of the ownership of livestock is still negatively related to the incidence of hazardous child labour, it is diminished.

The Multinomial logit model in Table C.12 considers a specific two-stage decision process in which three labour outcomes are compared; "No Work", "Non-Hazardous Work" and "Hazardous Work". The marginal effects in the Table represent the probability of each determinant to increase the choice of "Non-Hazardous Work", and "Hazardous Work". The comparison group is "No Work". The coefficients from the multinomial logit model are in line with the results of the sequential logit model. As the interest of this study is hazardous forms of child labour, this section only focuses on the results from Columns (6)-(12). Compared with non-working children, an increase in the wealth index reduces the probability of engaging in hazardous forms of child labour. Besides, The results from Table C.12 support the finding that being a child who lives with distant relatives increases the probability of working in hazardous environments, while it does not present any impact for non-hazardous child labour. Furthermore, the coefficient signs for father away or dead remain insignificant.

Table C.9: Sequential Logit Model on Child Labour and Hazardous Forms of Labour

	First Stage Sequential Logit					
	Child Labour					
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.116**	-0.115**	-0.102*	-0.0965*	-0.0974*	-0.126**
	(0.0399)	(0.0401)	(0.0404)	(0.0405)	(0.0405)	(0.0423)
Rural	0.634***	0.610***	0.625***	0.564***	0.564***	0.564***
	(0.123)	(0.119)	(0.121)	(0.121)	(0.121)	(0.121)
Household size	0.00669	0.0141	0.0355	0.0270	0.0268	0.0269
	(0.0122)	(0.0133)	(0.0204)	(0.0208)	(0.0208)	(0.0209)
Independent	0.0361	0.102	-0.0043	-0.0032	-0.00042	-0.0002
	(0.0684)	(0.0687)	(0.0708)	(0.0710)	(0.0709)	(0.0715)
Father away	-0.00774	-0.0170	-0.0229	-0.0183	-0.0199	-0.449
	(0.192)	(0.200)	(0.204)	(0.206)	(0.206)	(0.344)
Father dead	0.0564	0.0759	0.00192	0.0632	0.0360	-0.146
	(0.116)	(0.115)	(0.121)	(0.123)	(0.126)	(0.132)
Mother away	0.0375	0.0397	-0.0177	-0.0307	-0.0788	-0.277
	(0.207)	(0.211)	(0.212)	(0.213)	(0.277)	(0.383)
Mother dead	0.00236**	0.0158**	0.0254	0.0169	0.0322	0.476
	(0.140)	(0.140)	(0.143)	(0.142)	(0.179)	(0.273)
Has electricity	-0.167*	0.152	0.148	0.176	0.176	-0.195
	(0.0831)	(0.0990)	(0.101)	(0.102)	(0.102)	(0.160)
Has water	-0.691***	-0.445**	-0.474**	-0.459**	-0.460**	-0.0114
	(0.141)	(0.150)	(0.150)	(0.151)	(0.151)	(0.288)
Wealth Index		-0.281***	-0.302***	-0.302***	-0.301***	-0.302***
		(0.0401)	(0.0402)	(0.0401)	(0.0401)	(0.0401)
<5years			-0.253***	-0.247***	-0.246***	-0.247***
			(0.0392)	(0.0395)	(0.0395)	(0.0394)
6-14 years			0.0802*	0.0799*	0.0807*	0.0804*
			(0.0328)	(0.0326)	(0.0326)	(0.0326)
>60years			0.0482	0.0631	0.0550	0.0569
			(0.0591)	(0.0587)	(0.0587)	(0.0587)
Land(hectares)				0.00479**	0.00477**	0.00472**
				(0.00176)	(0.00177)	(0.00177)
(#) Livestock				-0.000814	-0.000836	-0.000913
				(0.00382)	(0.00382)	(0.00382)
(#) Horse & Donkey				-0.0339*	-0.0339*	-0.0344*
				(0.0147)	(0.0146)	(0.0147)
(#) Chicken				0.00720**	0.00718**	0.00722**
				(0.00254)	(0.00253)	(0.00253)
Independent Child × Grandparents					-0.356	
					(0.381)	
Independent Child × Female						-0.527
						(0.427)
Father away × Female						0.688
						(0.398)
Father dead × Female						0.410*
						(0.175)
Mother away × Female						-0.0124
						(0.254)
Mother dead × Female						-0.0743
						(0.202)
N	14347	14347	14347	14347	14347	14347

Table C.10: Sequential Logit Model on Child Labour and Hazardous Forms of Labour

	Second Stage Sequential Logit					
	Hazardous Forms of Labour					
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.248**	-0.255**	-0.260***	-0.260**	-0.259**	-0.288***
	(0.0782)	(0.0785)	(0.0790)	(0.0798)	(0.0796)	(0.0830)
Rural	0.751***	0.453*	0.462*	0.510*	0.510*	0.514*
	(0.191)	(0.223)	(0.220)	(0.221)	(0.221)	(0.221)
Household size	-0.0293	-0.0193	0.0213	0.0210	0.0215	0.0212
	(0.0244)	(0.0232)	(0.0372)	(0.0365)	(0.0365)	(0.0365)
Independent	0.014*	0.011*	0.023*	0.025*	0.025*	0.043*
	(0.141)	(0.138)	(0.136)	(0.138)	(0.138)	(0.139)
Father away	0.0280	0.0897	0.0961	0.184	0.182	-0.331
	(0.355)	(0.356)	(0.359)	(0.368)	(0.368)	(0.547)
Father dead	0.0280	0.0897	0.0961	0.184	0.182	-0.331
	(0.208)	(0.217)	(0.214)	(0.221)	(0.229)	(0.265)
Mother away	-0.275	-0.234	-0.184	-0.186	0.187	0.186
	(0.380)	(0.380)	(0.379)	(0.468)	(0.380)	(0.408)
Mother dead	0.467	0.471	0.514	0.452	0.413	0.435
	(0.269)	(0.272)	(0.269)	(0.368)	(0.269)	(0.368)
Has electricity	0.196	0.186	0.175	0.174	0.183	0.184
	(0.187)	(0.189)	(0.190)	(0.190)	(0.190)	(0.190)
Has water	0.271	0.270	0.254	0.249	0.232	0.244
	(0.298)	(0.298)	(0.299)	(0.299)	(0.269)	(0.296)
Wealth Index	-0.248**	-0.253**	-0.246**	-0.246**	-0.246**	
		(0.0827)	(0.0821)	(0.0810)	(0.0810)	(0.0810)
<5years			0.0298	0.0413	0.0403	0.0412
			(0.0698)	(0.0699)	(0.0700)	(0.0700)
6-14 years			-0.117	-0.0863	-0.0874	-0.0878
			(0.0679)	(0.0628)	(0.0628)	(0.0627)
>60years			0.00256	0.00908	0.00973	0.00736
			(0.109)	(0.111)	(0.111)	(0.111)
Land(hectares)				-0.00375**	-0.00373**	-0.00375**
				(0.00361)	(0.00361)	(0.00364)
(#) Livestock				-0.0568*	-0.0570*	-0.0576*
				(0.0755)	(0.0755)	(0.0755)
(#) Horse & Donkey				-0.440*	-0.440*	-0.443*
				(0.209)	(0.209)	(0.210)
(#) Chicken				-0.00801	-0.00793	-0.00794
				(0.00420)	(0.00421)	(0.00423)
Independent Child × Grandparents					0.469	
					(0.535)	
Independent Child × Female						-0.752
						(0.663)
Father away × Female						0.872
						(0.724)
Father dead × Female						0.154
						(0.328)
Mother away × Female						-0.310
						(0.469)
Mother dead × Female						0.567
						(0.356)
N	14347	14347	14347	14347	14347	14347

Table C.11: Robustness Checks: LPM on Child Labour and Hazardous Forms of Labour

	LPM Child Labour						LPM Hazardous Forms of Labour					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.0218**	-0.0214**	-0.0189**	-0.0178*	-0.0178*	-0.0237**	-0.0282***	-0.0278***	-0.0261***	-0.0253***	-0.0253***	-0.0297***
	(-3.02)	(-2.97)	(-2.64)	(-2.50)	(-2.50)	(-3.14)	(-4.30)	(-4.26)	(-4.03)	(-3.91)	(-3.91)	(-4.32)
Rural	0.142***	0.0991***	0.101***	0.0900***	0.0901***	0.0901***	0.131***	0.0897***	0.0914***	0.0836***	0.0840***	0.0840***
	(14.74)	(9.44)	(9.67)	(8.55)	(8.56)	(8.56)	(15.91)	(10.00)	(10.18)	(9.22)	(9.26)	(9.27)
Household size	0.00159	0.00255**	0.00649***	0.00485**	0.00487**	0.00487**	-0.000541	0.000388	0.00521***	0.00429**	0.00434**	0.00435**
	(1.64)	(2.60)	(3.80)	(2.80)	(2.81)	(2.81)	(-0.67)	(0.47)	(3.52)	(2.86)	(2.90)	(2.90)
Independent	0.0148	0.0138	0.00431	0.00823	0.00818	0.00829	0.0112	0.0103	0.00272	0.00579	0.00563	0.00742
	(1.06)	(1.00)	(0.31)	(0.60)	(0.59)	(0.59)	(0.91)	(0.84)	(0.22)	(0.47)	(0.45)	(0.59)
Mother away	-0.00446	0.00277	-0.00963	-0.0132	-0.0132	-0.0126	-0.00759	-0.000616	-0.00900	-0.0121	-0.0122	-0.0131
	(-0.37)	(0.23)	(-0.80)	(-1.10)	(-1.10)	(-1.03)	(-0.70)	(-0.06)	(-0.83)	(-1.12)	(-1.13)	(-1.19)
Mother dead	-0.0242	-0.0192	-0.0303	-0.0176	-0.0177	-0.0239	-0.00685	-0.00212	-0.0108	0.00102	0.000862	-0.0108
	(-1.27)	(-1.01)	(-1.61)	(-0.91)	(-0.91)	(-0.93)	(-0.40)	(-0.12)	(-0.62)	(0.06)	(0.05)	(-0.45)
Father away	-0.00278	0.00169	-0.00545	-0.00484	-0.00480	-0.0701	-0.00597	-0.00166	-0.00606	-0.00492	-0.00481	-0.0713*
	(-0.11)	(0.07)	(-0.21)	(-0.19)	(-0.19)	(-1.72)	(-0.26)	(-0.07)	(-0.26)	(-0.21)	(-0.21)	(-2.11)
Father dead	0.0136	0.0118	0.00320	0.0124	0.0123	-0.0238	0.000502	-0.00116	-0.00771	0.000120	-0.000374	-0.0201
	(0.88)	(0.77)	(0.21)	(0.79)	(0.78)	(-1.15)	(0.04)	(-0.08)	(-0.56)	(0.01)	(-0.03)	(-1.07)
Has electricity	0.0367***	0.0247*	0.0242*	0.0294**	0.0293**	0.0288**	-0.0376***	0.0215*	0.0213*	0.0240*	0.0239*	0.0233*
	(3.96)	(2.23)	(2.21)	(2.68)	(2.67)	(2.62)	(-4.45)	(2.13)	(2.12)	(2.39)	(2.38)	(2.32)
Has water	-0.0921***	-0.0466***	-0.0510***	-0.0474***	-0.0475***	-0.0477***	-0.0582***	-0.0144	-0.0179*	-0.0152	-0.0155	-0.0158
	(-9.40)	(-4.40)	(-4.84)	(-4.48)	(-4.48)	(-4.50)	(-6.96)	(-1.59)	(-1.98)	(-1.68)	(-1.71)	(-1.74)
Wealth Index		-0.0523***	-0.0546***	-0.0559***	-0.0558***	-0.0557***		-0.0504***	-0.0522***	-0.0534***	-0.0531***	-0.0529***
		(-10.36)	(-10.94)	(-11.26)	(-11.23)	(-11.19)		(-11.18)	(-11.65)	(-11.93)	(-11.85)	(-11.80)
<5years			-0.0470***	-0.0457***	-0.0457***	-0.0458***			-0.0338***	-0.0331***	-0.0331***	-0.0332***
			(-13.41)	(-13.02)	(-13.02)	(-13.05)			(-10.54)	(-10.31)	(-10.31)	(-10.33)
6-14years			0.0152***	0.0149***	0.0150***	0.0150***			0.00508	0.0048	0.005	0.005
			(5.04)	(4.99)	(4.99)	(5.01)			(1.93)	(1.83)	(1.86)	(1.88)
>60years			0.00975	0.0115	0.0115	0.0106			0.0115*	0.0128*	0.0128*	0.0120*
			(1.61)	(1.90)	(1.90)	(1.75)			(2.11)	(2.34)	(2.35)	(2.19)
Land(hectares)				0.0009***	0.0009***	0.0009***				0.0009***	0.0009***	0.0009***
				(4.56)	(4.58)	(4.50)				(4.87)	(4.95)	(4.89)
Livestock				-0.0002	-0.0002	-0.0002				-0.0005	-0.0005	-0.0005
				(-0.45)	(-0.46)	(-0.50)				(-1.56)	(-1.58)	(-1.62)
(#) Horse & Donkey				-0.00304***	-0.003***	-0.00295***				-0.00204***	-0.00166***	-0.00167***
				(-9.34)	(-6.72)	(-6.77)				(-8.17)	(-4.73)	(-4.70)
(#) Chicken				0.002***	0.002***	0.00156***				0.0007**	0.0008**	0.0008**
				(5.68)	(5.63)	(5.65)				(2.82)	(3.02)	(3.02)
Independent Child × Grandparents					-0.185**						-0.174***	
					(-3.00)						(-3.53)	
Independent Child × Female						-0.0871						-0.121*
						(-1.38)						(-2.32)
Father away × Female						0.106*						0.114*
						(1.98)						(2.45)
Father dead × Female						0.0701*						0.0439
						(2.27)						(1.60)
Mother away × Female						-0.00147						-0.0211
						(-0.04)						(-0.62)
Mother dead × Female						0.0103						0.0303
						(0.26)						(0.81)
N	3900	3900	3900	3900	3900	3900	2840	2840	2840	2840	2840	2840

Table C.12: Robustness checks: Multinomial Logit on Child Labour and Hazardous Forms of Labour

	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
			Non Hazardous Labour						Hazardous Labour			
No_work (base)												
Female	0.0564	0.0567	0.0705	0.0731	0.0730	0.0458	-0.184***	-0.185***	-0.174***	-0.167***	-0.167***	-0.200***
	(0.86)	(0.87)	(1.07)	(1.11)	(1.11)	(0.66)	(-4.15)	(-4.13)	(-3.86)	(-3.71)	(-3.70)	(-4.20)
Rural	0.381***	0.303**	0.317**	0.246*	0.240*	0.238*	1.076***	0.792***	0.811***	0.758***	0.761***	0.762***
	(4.00)	(2.91)	(3.04)	(2.36)	(2.31)	(2.29)	(14.23)	(9.91)	(10.05)	(9.31)	(9.33)	(9.34)
Household size	0.0284***	0.0303***	0.0291*	0.0173	0.0175	0.0177	-0.00199	0.00555	0.0393***	0.0313**	0.0316**	0.0315**
	(3.59)	(3.82)	(2.00)	(1.17)	(1.18)	(1.19)	(-0.37)	(1.02)	(3.56)	(2.82)	(2.86)	(2.83)
Independent	0.0183	0.0171	-0.0376	-0.0202	-0.0193	-0.0421	0.120	0.122	0.0696	0.0902	0.0886	0.101
	(0.14)	(0.13)	(-0.29)	(-0.15)	(-0.15)	(-0.32)	(1.35)	(1.37)	(0.76)	(0.99)	(0.97)	(1.09)
Mother away	0.109	0.123	0.0401	0.0247	0.0248	0.0476	-0.0762	-0.0293	-0.0875	-0.104	-0.105	-0.110
	(0.98)	(1.10)	(0.36)	(0.22)	(0.22)	(0.43)	(-0.98)	(-0.37)	(-1.10)	(-1.31)	(-1.32)	(-1.36)
Mother dead	-0.243	-0.234	-0.305	-0.269	-0.270	-0.306	-0.0826	-0.0440	-0.110	-0.0128	-0.0120	-0.0346
	(-1.31)	(-1.26)	(-1.64)	(-1.43)	(-1.43)	(-1.16)	(-0.68)	(-0.36)	(-0.89)	(-0.10)	(-0.10)	(-0.21)
Father away	-0.0575	-0.0467	-0.108	-0.130	-0.134	-0.218	-0.00905	0.0343	0.0143	0.0209	0.0221	-0.593
	(-0.21)	(-0.17)	(-0.40)	(-0.48)	(-0.50)	(-0.49)	(-0.05)	(0.18)	(0.07)	(0.11)	(0.11)	(-1.67)
Father dead	0.128	0.124	0.0837	0.119	0.126	-0.0762	0.0491	0.0451	-0.00842	0.0566	0.0526	-0.138
	(0.98)	(0.95)	(0.63)	(0.88)	(0.94)	(-0.39)	(0.51)	(0.47)	(-0.09)	(0.58)	(0.54)	(-1.06)
Has electricity	-0.0628	0.0524	0.0459	0.0840	0.0841	0.0886	-0.206***	0.195**	0.192**	0.220***	0.218***	0.216***
	(-0.80)	(0.57)	(0.49)	(0.89)	(0.89)	(0.94)	(-4.02)	(3.15)	(3.07)	(3.50)	(3.48)	(3.43)
Has water	-0.721***	-0.638***	-0.664***	-0.643***	-0.638***	-0.639***	-0.684***	-0.361***	-0.386***	-0.372***	-0.375***	-0.375***
	(-5.67)	(-4.80)	(-4.96)	(-4.78)	(-4.73)	(-4.73)	(-6.87)	(-3.44)	(-3.67)	(-3.53)	(-3.55)	(-3.56)
Wealth Index		-0.0985*	-0.111*	-0.121**	-0.125**	-0.127**		-0.356***	-0.372***	-0.381***	-0.379***	-0.378***
		(-2.16)	(-2.45)	(-2.68)	(-2.78)	(-2.81)		(-11.29)	(-11.80)	(-12.06)	(-11.98)	(-11.92)
<5years			-0.272***	-0.266***	-0.267***	-0.268***			-0.252***	-0.245***	-0.245***	-0.246***
			(-8.46)	(-8.22)	(-8.25)	(-8.28)			(-10.52)	(-10.21)	(-10.23)	(-10.26)
6-14 years			0.144***	0.145***	0.144***	0.143***			0.0493**	0.0518**	0.0519**	0.0526**
			(5.41)	(5.53)	(5.47)	(5.47)			(2.64)	(2.74)	(2.75)	(2.78)
>60years			0.0424	0.0522	0.0500	0.0473			0.0545	0.0708	0.0714	0.0628
			(0.82)	(1.01)	(0.97)	(0.92)			(1.48)	(1.92)	(1.94)	(1.71)
Land(hectares)				0.00188	0.00166	0.00157				0.00576***	0.00583***	0.00577***
				(1.01)	(0.88)	(0.83)				(5.36)	(5.43)	(5.37)
(#)Livestock				0.00370	0.00373	0.00367				-0.00290	-0.00292	-0.00297
				(1.24)	(1.25)	(1.23)				(-1.34)	(-1.37)	(-1.39)
(#) Horse& donkey				-0.0264***	-0.0303***	-0.0303***				-0.160*	-0.137	-0.137
				(-5.60)	(-6.10)	(-6.14)				(-2.01)	(-1.68)	(-1.69)
(#) Chicken				0.0117***	0.0113***	0.0113***				0.00582***	0.00613***	0.00617***
				(6.43)	(5.92)	(5.92)				(4.01)	(4.17)	(4.20)
Independent Child × Grandparents					-0.562						-1.650**	
					(-0.72)						(-2.59)	
Independent Child × Female						0.338						-0.969*
						(0.62)						(-1.98)
Father away × Female						0.0526						1.019*
						(0.09)						(2.36)
Father dead × Female						0.295						0.410*
						(1.11)						(2.15)
Mother away × Female						0.251						-0.152
						(0.80)						(-0.58)
Mother dead × Female						-0.103						0.0633
						(-0.25)						(0.24)

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.13: Robustness Check: LPM on Emotional and Physical Child Abuse

	Emotional Abuse						Mild Physical Abuse						Extreme Physical Abuse					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.00256	-0.00233	-0.00245	-0.00225	-0.00225	-0.00484	-0.0120	-0.0118	-0.0134	-0.0136	-0.0136	-0.0141	-0.0231**	-0.0230**	-0.0235***	-0.0237***	-0.0237***	-0.0290***
	(-0.36)	(-0.33)	(-0.35)	(-0.32)	(-0.32)	(-0.65)	(-1.47)	(-1.44)	(-1.64)	(-1.66)	(-1.66)	(-1.63)	(-3.28)	(-3.26)	(-3.33)	(-3.36)	(-3.36)	(-3.85)
Rural	0.0408***	0.0148	0.0107	0.00839	0.00839	0.00811	0.0194	-0.00731	-0.0123	-0.0119	-0.0119	-0.0115	0.0255**	0.00821	0.00682	0.00987	0.00987	0.0101
	(4.02)	(1.34)	(0.97)	(0.75)	(0.75)	(0.73)	(1.69)	(-0.59)	(-0.99)	(-0.95)	(-0.95)	(-0.92)	(2.63)	(0.79)	(0.66)	(0.95)	(0.95)	(0.97)
Household size	0.0683***	0.0625***	0.0238***	0.0241***	0.0241***	0.0240***	0.0230*	0.0170	0.0202***	0.0205***	0.0205***	0.0206***	0.0198*	0.0159*	0.0655***	0.0595***	0.0595***	0.0601***
	(7.28)	(6.63)	(13.23)	(13.30)	(13.30)	(13.28)	(2.20)	(1.61)	(10.42)	(10.54)	(10.54)	(10.56)	(2.48)	(1.99)	(4.20)	(3.79)	(3.79)	(3.82)
Independent	0.0361**	0.0366**	0.0401**	0.0389**	0.0389**	0.0420**	0.0278**	0.0284**	0.0251***	0.0243**	0.0243*	0.0212***	0.0122**	0.0125*	0.0116**	0.0116**	0.0116**	0.00734**
	(2.63)	(2.68)	(2.92)	(2.82)	(2.82)	(3.01)	(1.71)	(1.74)	(1.54)	(1.49)	(1.49)	(1.28)	(0.89)	(0.92)	(0.84)	(0.84)	(0.84)	(0.52)
Mother away	0.0113	0.0156	0.0156	0.0144	0.0144	0.0174	-0.0410**	-0.0365**	-0.0292*	-0.0299*	-0.0299*	-0.0323*	-0.00651	-0.00361	-0.00134	-0.00155	-0.00155	-0.00475
	(0.96)	(1.33)	(1.33)	(1.22)	(1.22)	(1.46)	(-2.90)	(-2.58)	(-2.06)	(-2.11)	(-2.11)	(-2.25)	(-0.54)	(-0.30)	(-0.11)	(-0.13)	(-0.13)	(-0.39)
Mother dead	-0.0380	-0.0351	-0.0324	-0.0250	-0.0250	-0.0263	-0.106***	-0.103***	-0.0937***	-0.0838***	-0.0838***	-0.105***	-0.0656***	-0.0636***	-0.0610***	-0.0559**	-0.0559**	-0.0508*
	(-1.94)	(-1.78)	(-1.65)	(-1.25)	(-1.25)	(-0.95)	(-4.82)	(-4.69)	(-4.30)	(-3.72)	(-3.72)	(-3.47)	(-3.93)	(-3.81)	(-3.64)	(-3.22)	(-3.22)	(-2.14)
Father away	0.0180	0.0207	0.0176	0.0169	0.0169	-0.00456	-0.0239	-0.0211	-0.0198	-0.0237	-0.0237	-0.0805	-0.0311	-0.0294	-0.0288	-0.0289	-0.0289	-0.0857*
	(0.64)	(0.74)	(0.63)	(0.60)	(0.60)	(-0.10)	(-0.75)	(-0.66)	(-0.63)	(-0.75)	(-0.75)	(-1.56)	(-1.23)	(-1.15)	(-1.13)	(-1.13)	(-1.13)	(-2.31)
Father dead	0.00271	0.00166	0.00248	0.00724	0.00724	-0.0129	-0.0128	-0.0139	-0.00768	-0.00106	-0.00106	0.00218	-0.00583	-0.00652	-0.00473	-0.00261	-0.00261	-0.0385
	(0.18)	(0.11)	(0.16)	(0.48)	(0.48)	(-0.61)	(-0.74)	(-0.80)	(-0.45)	(-0.06)	(-0.06)	(0.09)	(-0.40)	(-0.45)	(-0.32)	(-0.17)	(-0.17)	(-1.94)
Has electricity	-0.0269**	0.0102	0.00781	0.00863	0.00863	0.00881	-0.0201*	0.0180	0.0163	0.0171	0.0171	0.0165	-0.0133	0.0114	0.0109	0.00893	0.00893	0.00793
	(-3.25)	(1.00)	(0.77)	(0.85)	(0.85)	(0.87)	(-2.05)	(1.51)	(1.36)	(1.43)	(1.43)	(1.38)	(-1.54)	(1.11)	(1.06)	(0.87)	(0.87)	(0.77)
Has water	-0.00910	0.0184	0.0217	0.0231	0.0231	0.0229	-0.0104	0.0179	0.0237	0.0250	0.0250	0.0245	-0.00945	0.00880	0.0104	0.00974	0.00974	0.00981
	(-0.75)	(1.41)	(1.68)	(1.79)	(1.79)	(1.77)	(-0.78)	(1.25)	(1.66)	(1.75)	(1.75)	(1.71)	(-0.87)	(0.75)	(0.89)	(0.83)	(0.83)	(0.84)
Wealth Index		-0.0316***	-0.0281***	-0.0285***	-0.0285***	-0.0286***		-0.0326***	-0.0281***	-0.0280***	-0.0280***	-0.0277***		-0.0210***	-0.0197***	-0.0196***	-0.0196***	-0.0193***
		(-6.16)	(-5.49)	(-5.56)	(-5.56)	(-5.57)		(-5.60)	(-4.83)	(-4.81)	(-4.81)	(-4.76)		(-4.42)	(-4.14)	(-4.10)	(-4.10)	(-4.05)
<5years			0.0272***	0.0274***	0.0274***	0.0274***			0.0521***	0.0522***	0.0522***	0.0522***			0.0151***	0.0146***	0.0146***	0.0144***
			(7.77)	(7.82)	(7.82)	(7.82)			(13.24)	(13.28)	(13.28)	(13.29)			(4.28)	(4.13)	(4.13)	(4.08)
6-14years			0.0319***	0.0318***	0.0318***	0.0318***			0.0213***	0.0213***	0.0213***	0.0215***			0.00500	0.00490	0.00490	0.00498
			(10.47)	(10.42)	(10.42)	(10.42)			(6.27)	(6.27)	(6.27)	(6.33)			(1.75)	(1.72)	(1.72)	(1.75)
>60years			0.0145*	0.0152*	0.0152*	0.0146*			0.00390	0.00486	0.00486	0.00402			0.00154	0.00162	0.00162	0.00122
			(2.45)	(2.56)	(2.56)	(2.47)			(0.57)	(0.71)	(0.71)	(0.59)			(0.26)	(0.27)	(0.27)	(0.21)
Land(hectares)				0.000315	0.000315	0.000307				-0.000214	-0.000214	-0.000212				-0.0000458	-0.0000458	-0.0000540
				(1.76)	(1.76)	(1.72)				(-0.96)	(-0.96)	(-0.96)				(-0.24)	(-0.24)	(-0.28)
(#) Livestock				0.000254	0.000243	0.000242				0.000122	0.000123	0.000122				-0.0003	-0.0003	-0.0003
				(0.54)	(0.54)	(0.52)				(1.14)	(1.14)	(1.15)				(-1.36)	(-1.36)	(-1.33)
(#) Horse & donkey				0.000295	0.000295	0.000220				0.00239*	0.00239*	0.00246*				0.000771	0.000771	0.000792
				(0.29)	(0.29)	(0.22)				(2.46)	(2.46)	(2.55)				(0.78)	(0.78)	(0.80)
(#) Chicken				0.000199	0.000199	0.000195				0.000388	0.000388	0.000387				-0.000660**	-0.000660**	-0.000652**
				(0.83)	(0.83)	(0.82)				(1.37)	(1.37)	(1.37)				(-2.76)	(-2.76)	(-2.73)
Independent Child × Grandparents				-0.116	-0.116					-0.165*	-0.165*					-0.0816	-0.0816	
				(-1.46)	(-1.46)					(-2.23)	(-2.23)					(-1.59)	(-1.59)	
Independent Child × Female						-0.000762						-0.0164						-0.0949
						(-0.01)						(-0.23)						(-1.86)
Father away × Female						0.0211						0.119						0.112*
						(0.36)						(1.81)						(2.21)
Father dead × Female						0.0298						-0.0125						0.0816**
						(0.99)						(-0.36)						(2.77)
Mother away × Female						0.0396						-0.0756						-0.0595
						(1.10)						(-1.68)						(-1.75)
Mother dead × Female						-0.0104						0.0239						-0.000143
						(-0.25)						(0.51)						(-0.00)
N	14347	14347	14347	14347	14347	14347	14347	14347	14347	14347	14347	14347	14347	14347	14347	14347	14347	14347

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Bibliography

Abou, P. E. (2019). A re-examination of the determinants of child labour in côte d'ivoire. pages 26–35.

Ademe, F., Kibret, K., Beyene, S., Getinet, M., and Mitike, G. (2019). Rainfall analysis for rain-fed farming in the Great Rift Valley Basins of Ethiopia. *Journal of Water and Climate Change*. jwc2019242.

Afifi, T. O., Mota, N., Sareen, J., and MacMillan, H. L. (2017). The relationships between harsh physical punishment and child maltreatment in childhood and intimate partner violence in adulthood. *BMC Public Health*, 17(1):493.

Ahlerup, P., Baskaran, T., and Bigsten, A. (2019). Gold mining and education: A long-run resource curse in africa? *The Journal of Development Studies*, pages 1–18.

Andersson, M., Hall, O., and Boke-Olén, N. (2015). Mining, economic activity and remote sensing: Case studies from burkina faso, ghana, mali and tanzania",. In *CSAE Conference 2015: Economic Development in Africa*, pages –42. The Centre for the Study of African Economies (CSAE), Department of Economics at Oxford University.

Aragón, F. M. and Rud, J. P. (2013). Natural resources and local communities: Evidence from a peruvian gold mine. *American Economic Journal: Economic Policy*, 5(2):1–25.

Aragón, F. M. and Rud, J. P. (2016). Polluting industries and agricultural productivity: Evidence from mining in ghana. *The Economic Journal*, 126(597):1980–2011.

Asrat, D. and Anteneh, A. (2019). The determinants of irrigation participation and its impact on the pastoralist and agro-pastoralists income in ethiopia: A review study. *Cogent Food & Agriculture*, 5(1):1679700.

Atteraya, M. S., Ebrahim, N. B., and Gnawali, S. (2018). Determinants of child maltreatment in nepal: Results from the 2014 nepal multiple indicator cluster survey (the 2014 nmics). *Child Abuse Neglect*, 76:400 – 407.

Awlachew, S., Yilma, A., Loulseged, M., Loiskandl, W., Ayana, M., and Alamirew, T. (2007). Water resources and irrigation development in ethiopia.

Awulachew, S. B. (2019). Irrigation potential in ethiopia: constraints and opportunities for enhancing the system. *Gates Open Res*, 3:22.

Axbard, S., Poulsen, J., and Benshaul-Tolonen, A. (2019). Extractive industries, price shocks and criminality.

Bannock, L. C. (2005). Vulnerability of artisanal and small scale mining to commodity price fluctuation. Technical report.

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

Bazillier, R. and Girard, V. (2020). The gold digger and the machine. evidence on the distributive effect of the artisanal and industrial gold rushes in burkina faso. *Journal of Development Economics*, 143:102411.

Beegle, K., Dehejia, R. H., and Gatti, R. (2006). Child labor and agricultural shocks. *Journal of Development Economics*, 81(1):80 – 96.

Bhalotra, S. (2002). Parent altruism.

Bhalotra, S. and Heady, C. (2003). Child farm labor: The wealth paradox. Bristol Economics Discussion Papers 03/553, School of Economics, University of Bristol, UK.

Blanc, E. and Strobl, E. (2014). Is small better? a comparison of the effect of large and small dams on cropland productivity in south africa. *The World Bank Economic Review*, 28(3):545–576.

Blay-Tofey, M. and Lee, B. X. (2015). Preventing gender-based violence engendered by conflict: The case of côte d'ivoire. *Social Science & Medicine*, 146:341–347.

Brewer, M. and O'Dea, C. (2012). Measuring living standards with income and consumption: Evidence from the uk. ISER Working Paper Series 2012-05, Colchester.

Brooks-Gunn, J. and Duncan, G. J. (1997). The effects of poverty on children. *The Future of Children*, 7(2):55–71.

Caeser-Leo, M. (1999). Child labour: the most visible type of child abuse and neglect in india. *Child Abuse Review*, 8(2):75–86.

Caldwell, J. and Caldwell, P. (1993). Roles of women families and communities in preventing illness and providing health services in developing countries.

Case, A., Paxson, C., and Ableidinger, J. (2004). Orphans in africa: parental death, poverty, and school enrollment. *Demography*, 41(3):483–508.

Coates, A. A. and Messman-Moore, T. L. (2014). A structural model of mechanisms predicting depressive symptoms in women following childhood psychological maltreatment. *Child Abuse Neglect*, 38(1):103 – 113.

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*, 16:519–563.

Cogneau, D. and Jedwab, R. (2012). Commodity price shocks and child outcomes: The 1990 cocoa crisis in côte d'ivoire. *Economic Development and Cultural Change*, 60(3):507–534.

Colmer, J. (2013). Climate variability, child labour and schooling: Evidence on the intensive and extensive margin. Nota di Lavoro 81.2013, Grantham Research Institute on Climate Change and the Environment, Milano.

DeGraff, D. S., Ferro, A. R., and Levison, D. (2014). Kids at risk: children's employment in hazardous occupations in brazil. *Estudos Econômicos (São Paulo)*, 44(4):685–721.

Desanker, P. and Magadza, C. (2001). Climate change in africa: impacts, adaptation and vulnerability.

Di Falco, S., Yesuf, M., Kohlin, G., and Ringler, C. (2012). Estimating the impact of climate change on agriculture in low-income countries: Household level evidence from the nile basin, ethiopia. *Environmental and Resource Economics*, 52.

Diallo, Y. (2001). Les déterminants du travail des enfants en Côte d'Ivoire. Documents de travail 55, Groupe d'Economie du Développement de l'Université Montesquieu Bordeaux IV.

Diané Baba, Diallo Thierno Brahima, D. M. (2015). Rapport de l'etude diagnostique de la question enseignante en république du mali. Technical report, Bureau National au Mali.

Duflo, E. and Pande, R. (2007). Dams. *The Quarterly Journal of Economics*, 122(2):601–646.

Edmonds, E. V. (2008). Defining child labor: A review of the definitions of child labor used in academic and policy research. In Chenery, H. and Srinivasan, T. N., editors, *Handbook of Development Economics*. Elsevier.

Edmonds, E. V. (2010). *Selection into worst forms of child labor*, volume 31, pages 1–31.

Edmonds, E. V. and Shrestha, M. (2012). Child labor migrants and children outside of parental care. Technical report, Working Paper. Available online at: http://www. iza. org/MigrationHandbook . . . .

Evan, P. and Pankhurst, B. (1994). *Ethiopian village studies. Edited & produced jointly by the Department of Sociology, Addis Ababa University, Ethiopia & the Centre for the Study of African Economies*. Oxford.

Gilbert, R., Widom, C. S., Browne, K., Fergusson, D., Webb, E., and Janson, S. (2009). Burden and consequences of child maltreatment in high-income countries. *The Lancet*, 373(9657):68 – 81.

Grimm, M. and Gräb, J. (2011). Inequality in burkina faso—to what extent do household, community and regional factors matter? *Journal of the Royal Statistical Society Series A*, 174:759–784.

Grootaert, C. (1998). Child labor in cote d'ivoire: Incidence and determinants. *World Bank Policy Research*.

Guarcello, L., Lyon, S., and Rosati, F. (2004). Child labour and access to basic services: Evidence from five countries. *SSRN Electronic Journal*.

Guarcello, L., Mealli, F., and Rosati, F. C. (2010). Household vulnerability and child labor: the effect of shocks, credit rationing, and insurance. *Journal of Population Economics*, 23(1):169–198.

Günther, M. (2018). Local effects of artisanal mining: Empirical evidence from ghana.

Gylfason, T. (2001). Natural resources, education, and economic development. *European Economic Review*, 45(4):847 – 859. 15th Annual Congress of the European Economic Association.

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., and Townshend, J. R. G. (2013). High-resolution global maps of 21st-century forest cover change. *Science*, 342(6160):850–853.

Harris, M. G., Hulseberg, P., Ling, C., Karman, J., Clarkson, B. D., Harding, J. S., Zhang, M., Sandor, A., Christensen, K., Nagy, A., Sandor, M., and Fabry, Z. (2014). Immune privilege of the cns is not the consequence of limited antigen sampling. *Scientific Reports*, 4(1):4422.

Hilson, G. (2009). Small-scale mining, poverty and economic development in sub-saharan africa: An overview. *Resources Policy*, 34(1):1 – 5. Small-Scale Mining, Poverty and Development in Sub-Saharan Africa.

Hilson, G. (2012). Family hardship and cultural values: Child labor in malian small-scale gold mining communities. *World Development*, 40(8):1663 – 1674.

Hilson, G. (2016). Farming, small-scale mining and rural livelihoods in sub-saharan africa: A critical overview. *The Extractive Industries and Society*, 3(2):547 – 563.

Hirvonen, K. and Hoddinott, J. (2020). Beneficiary Views on Cash and In-Kind Payments: Evidence from Ethiopia's Productive Safety Net Programme. *The World Bank Economic Review*. lhaa002.

Hough, J. (1989). Inefficiency in education—the case of mali. *Comparative education*, 25(1):77–85.

Hulme, M., Doherty, R., Ngara, T., New, M., and Lister, D. (2005). Global warming and african climate change: a reassessment. *Climate change and Africa*, pages 29–40.

Hulme, M., RM, D., Ngara, T., New, M., and Lister, D. (2001). African climate change: 1900-2100. *CLIMATE RESEARCH*, 17:145–168.

Ito, T. and Kurosaki, T. (2009). Weather Risk, Wages in Kind, and the Off-Farm Labor Supply of Agricultural Households in a Developing Country. *American Journal of Agricultural Economics*, 91(3):697–710.

Jacoby, H. G. and Skoufias, E. (1998). Testing Theories of Consumption Behavior Using Information on Aggregate Shocks: Income Seasonality and Rainfall in Rural India. *American Journal of Agricultural Economics*, 80(1):1–14.

Jones, P. D. and Hulme, M. (1996). Calculating regional climatic time series for temperature and precipitation: methods and illustrations. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 16(4):361–377.

Kamei, A. (2018). Parental absence and agency: The household characteristics of hazardous forms of child labour in nepal. *Journal of International Development*, 30(7):1116–1141.

Katsanos, D., Retalis, A., Tymvios, F., and Michaelides, S. (2016). Analysis of precipitation extremes based on satellite (chirps) and in situ dataset over cyprus. *Natural Hazards*, 83(1):53–63.

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):50–61.

Kofol, C. and Ciarli, T. (2017). Child labor and conflict: Evidence from afghanistan. *Discussion Papers on Development Policy*, (240).

Kondylis, F. and Manacorda, M. (2012). School proximity and child labor: Evidence from rural tanzania. *The Journal of Human Resources*, 47(1):32–63.

Kotsadam, A. and Tolonen, A. (2016). African mining, gender, and local employment. *World Development*, 83:325 – 339.

Kruger, D. I. (2007). Coffee production effects on child labor and schooling in rural brazil. *Journal of Development Economics*, 82(2):448 – 463.

Land, F. M. A. P. C.-P. B. C. (2015). *The Local Economic Impacts of Resource Abundance: What Have We Learned?* The World Bank.

Land, P. C.-P. A. L. D. B. C. (2017). *Mining in Africa: Are Local Communities Better Off?* The World Bank.

Lertamphainont, S. and Sparrow, R. (2016). The Economic Impacts of Extreme Rainfall Events on Farming Households: Evidence from Thailand. PIER Discussion Papers 45, Puey Ungphakorn Institute for Economic Research.

Loayza, N. and Rigolini, J. (2016). The local impact of mining on poverty and inequality: Evidence from the commodity boom in peru. *World Development*, 84(C):219–234.

Macro, O. (2004). Demographic and health surveys. *Calverton, MD: ICF Macro*.

Maitra, P. and Tagat, A. (2019a). Labour supply responses to rainfall shocks.

Maitra, P. and Tagat, A. (2019b). Labour supply responses to rainfall shocks. *SSRN Electronic Journal*.

Markowitz, S. and Grossman, M. (1998). Alcohol regulation and domestic violence towards children. *Contemporary Economic Policy*, 16(3):309–320.

Markowitz, S. and Grossman, M. (2000). The effects of beer taxes on physical child abuse. *Journal of Health Economics*, 19(2):271–282.

McKee, T. B., Doesken, N. J., Kleist, J., et al. (1993). The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology*, volume 17, pages 179–183. Boston.

McLoyd, V. (1998). Socioeconomic disadvantage and child development. *The American psychologist*, 53(2):185—204.

Mejía, L. B. (2020). Mining and human capital accumulation: Evidence from the colombian gold rush. *Journal of Development Economics*, 145:102471.

Merrill, K. G., Smith, S. C., Quintero, L., and Devries, K. M. (2020). Measuring violence perpetration: Stability of teachers' self-reports before and after an anti-violence training in cote d'ivoire. *Child abuse & neglect*, 109:104687.

Mulligan, M., van Soesbergen, A., and Sáenz, L. (2020). Goodd, a global dataset of more than 38,000 georeferenced dams. *Scientific Data*, 7(1):31.

Murdock, G. P. (1959). Africa its peoples and their culture history.

NIPCCD (1988). National seminar on child abuse in india: A report. Technical report, National Institute of Public Cooperation and Child Development.

Norman, R., M, B., Rumna, D., Alexander, B., James, S., and Theo, V. (2012). The long-term health consequences of child physical abuse, emotional abuse, and neglect: A systematic review and meta-analysis. *Plos Medicine*.

Paternoster, R., BRAME, R., Mazerolle, P., and Piquero, A. (1998). Using the correct statistical test for equality of regression coefficients. *Criminology*, 36:859 – 866.

Paxson, C. and Waldfogel, J. (1999). Parental resources and child abuse and neglect. *The American Economic Review*, 89(2):239–244.

Paxson, C. and Waldfogel, J. (2002). Work, welfare, and child maltreatment. *Journal of Labor Economics*, 20(3):435–474.

Paxson, C. and Waldfogel, J. (2003). Welfare reforms, family resources, and child maltreatment. *Journal of Policy Analysis and Management*, 22(1):85–113.

Porter, C. (2012). Shocks, consumption and income diversification in rural ethiopia. *The Journal of Development Studies*, 48(9):1209–1222.

Ray, R. (2002). The determinants of child labor and child schooling in ghana. *Journal of African Economies*, 11:561–590.

Rose, E. (2001). Ex ante and ex post labor supply response to risk in a low-income area. *Journal of Development Economics*, 64(2):371–388.

Sanoh, A. and Massaoly, C. (2015). Socioeconomic and fiscal impact of large-scale gold mining in mali. *Policy Research working pape*, (WPS 7467).

Santos, R. (2014). Not all that glitters is gold: Gold boom, child labor and schooling in colombia. *SSRN Electronic Journal*.

Sarsons, H. (2011). Rainfall and conflict. In *Manuscript. http://www. econ. yale. edu/conference/neudc11/papers/paper_199. pdf*. Citeseer.

Silwal, A. R. (2016). Three essays on agriculture and economic development in Tanzania. Economics PhD Theses 1116, Department of Economics, University of Sussex Business School.

Smith, A., Vaux, T., and Development, U. (2003). Education, conflict and international development. *http://lst-iiep.iiep-unesco.org/cgi-bin/wwwi32.exe/[in=epidoc1.in]/?t2000=016476/(100)*.

Stichter, S. B. and Parpart, J. (1988). *Patriarchy and Class: African Women in the Home and the Workforce*. Routledge.

Strobl, E. and Strobl, R. (2011). The distributional impact of large dams: Evidence from cropland productivity in africa. *Journal of Development Economics*, 96:432–450.

Thomas, I. and Samassekou, S. (2003). Role of planted forests and trees outside forests in sustainable forest management: Republic of mali - country case study. Technical report, The Food and Agriculture Organization (FAO).

Thomas, S. (2010). Mining taxation: An application to mali. *International Monetary Fund, IMF Working Papers*, 10.

Trinh, T.-A., Posso, A., and Feeny, S. (2020). Child labor and rainfall deviation: Panel data evidence from rural vietnam. *The Developing Economies*, 58(1):63–76.

UNDP (2012). Rapport national sur le développement humain 2012 mali. Technical report, United Nations Development Program.

WHO (2016). Child maltreatment fact sheet. Technical report, World Health Organization.

Wickramasinghe, V. and Fernando, D. (2017). Use of microcredit for household income and consumption smoothing by low income communities. *International Journal of Consumer Studies*.

Woldenhanna, T. and Oskam, A. (2001). Income diversification and entry barriers: evidence from the tigray region of northern ethiopia. *Food Policy*, 26(4):351–365.

Zabsonré, A., Agbo, M., and Somé, J. (2018). Gold exploitation and socioeconomic outcomes: The case of burkina faso. *World Development*, 109(C):206–2011.