The Effect of Microinsurance on Child Work and Schooling: Evidence from northern Kenya and southern Ethiopia

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Abstract

We study the effects of index-based microinsurance on children's work and schooling using the Index-Based Livestock Insurance (IBLI), which targets pastoral households of Northern Kenya and Southern Ethiopia. The identification strategy uses randomly distributed discount coupons as an instrument for insurance coverage. Microinsurance shifts children's activity from work to schooling – the probability of a child engaged in part-time work decreased while the probability of a child being a full-time student increased. The insurance also protects children from increasing participation in livestock-related tasks during drought periods. These effects work through the changes in herding strategies where households become more transhumant and the substitution of child labor as buffer input during the drought. We find substantial heterogeneity across age, birth order and gender of a child.

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1 Introduction

Human capital investment is one of the critical drivers of economic development. However, poor households in developing countries often cannot make adequate investments in human capital because the direct cost of education and the opportunity cost of pulling children out of work can be unaffordable to these households (Todd and Wolpin, 2006; Basu and Van, 1998; Edmonds and Schady, 2012). Besides, poorer households with no or weaker risk-coping strategies are more vulnerable to adverse shocks such as droughts, animal/crop diseases, or illnesses that increase child labor (Beegle, Dehejia, and Gatti, 2006) and decrease child schooling (Björkman-Nyqvist, 2013). Access to capital markets such as insurance can alleviate these concerns, but these households often do not have access to formal insurance markets.

Agricultural insurance is a product that deals with a first-order concern that the households are exposed to the risk of losses that may drive them into poverty trap (Barnett, Barrett, and Skees, 2008; Jensen and Barrett, 2017). It has been shown that microinsurance mitigates these risks to some extent and improves the welfare of the insured household (Dercon and Christiaensen, 2011; Jensen, Barrett, and Mude, 2017; Janzen and Carter, 2019; Tafere, Barrett, and Lentz, 2019). However, it is not clear whether each household member enjoys improved welfare equally. Especially, the evidence on the effect of microinsurance on children of the insured household is thin. There is some evidence on the effects of health insurance on child labor and schooling (Landmann and Frölich, 2015; Frölich and Landmann, 2018; Guarcello, Mealli, and Rosati, 2010). These studies find that health insurance decreases children's work and increases educational attainment by protecting households from shock on adult labor. The type of microinsurance we study differs from health insurance since it decreases the uncertainty of the income, not the uncertainty of the factor of production. Hence, the effects of microinsurance on child outcomes are inherently different from that of health insurance. To our knowledge, this paper is the first evidence to study the relationship between agricultural insurance and children's work, schooling, the mechanism through which it works.

This paper examines the effects of index-based microinsurance on children's work and schooling using a microinsurance product launched in Arid and Semi-Arid Lands (ASAL) of Northern Kenya and Southern Ethiopia. We study the mechanism through which the effects work by examining related household outcomes such as herd size, household income, savings, and other risk coping strategies. Lastly, it aims to explain the results with a formal model. We use Index-Based Livestock Insurance (IBLI), which targets pastoral households comprising most of the region's population.

Arid and semi-arid lands of Northern Kenya and southern Ethiopia are where pastoral livelihood systems are dominant, with low educational attainment and high child labor rates. Pastoral households in the regions are driven into poverty traps due to catastrophic livestock losses triggered by droughts (Chantarat et al., 2017). One of the herding strategies is to mobilize the herd, but this and the remoteness of the region make the supply of education to these regions difficult. Due to an incomplete labor market, household members, especially children, are more likely to be used as a labor input. Moreover, due to the nature of the pastoral activities that require long hours of outside work, working children in pastoral regions work longer hours than the rest of the two countries.

IBLI is index-based insurance of which payout is determined based on the insurance area's index measure instead of individual loss. It uses Normalized-Differenced Vegetation Index (NDVI) and longitudinal household data on livestock mortality rates to construct the index. Since the NDVI index is based on satellite imageries and produced by an external organization, also at the area-aggregate level, the IBLI does not incur the cost of verifying individual loss claims. Moreover, at the household level, there is a lower probability of moral hazard or adverse selection. The effect of the insurance on the insured households' welfare is shown to be positive (Chantarat et al., 2013).

Our main data source is a panel survey containing comprehensive information about the herding strategies and demographic characteristics of 924 Kenyan households and 528 Ethiopian households over six rounds of surveys in Kenya and four rounds in Ethiopia. The survey was a part of the pilot program implemented to encourage the takeup of the insurance product and evaluate the welfare effect of the insurance. As part of the program, local insurance companies collaborated with researchers in International Livestock Research Institute (ILRI) and randomly provided discount coupons to the households with varying discount rates every sales season and collected survey data. In addition, we use administrative data of the insurance company on insurance takeup.

Our empirical strategy relies on the exogenous variation of insurance premiums paid by the households. The randomization was iterated every sales season, which occurs twice a year, providing a within-household variation on insurance premium. We estimate the effect of insurance exploiting this exogenous variation as an instrument. To ensure the validity of the instrument, We show that the random variation of the insurance premium was exogenous to a range of household and individual characteristics, and the instrument has a strong predictive power in the first stage.

Our main finding is that microinsurance shifts children's activity from work to schooling. The probability of a child working full-time decreased by 5.7 percentage points and simultaneously working and going to school by 10.4 percentage points, while the probability of a child being a full-time student increases by 12.6 percentage points. The effect is driven by children decreasing work as a secondary activity and household tasks, while children's work for livestock-related activities did not change on average.

We also find that the insurance helps children avoid being drawn to work upon adverse weather shocks. Children from uninsured households are more likely to be engaged in child labor in drought season by 8.8 percentage points compared to non-shock seasons, but the child labor of insured households on the drought seasons do not differ substantially from non-shock seasons.

Several potential mechanisms are ruled out after examining other household-level outcome variables such as livestock holdings and herding strategies. First, we find that the effect on neither the livestock holdings nor the diversification indicator is statistically significant. Therefore, it is difficult to claim that the changes in demand for child labor – either for livestock-related activities or other household income-generating activities – are the drivers. We also find that the households are more likely to be mobile due to insurance, ruling out the changes in the relative price of education to be the main driver. A likely dominating factor is the expected income effects induced by decreased risk of negative weather shock.

The effects are heterogeneous by birth order and by herd mobility. While the younger siblings decrease full-time work and livestock-related activities, the oldest siblings decrease part-time work, showing that the firstborns bear the burden to support their younger siblings financially. Mobile households decrease full-time work and livestock-related activities, while sedentary households decrease part-time work.

This paper contributes to the growing literature on the effects of microinsurance by adding rare evidence on the effect of microinsurance at the child level. The current literature on microinsurance products finds effects on welfare at the household level. Microinsurance products mitigate adverse effects from the shock (Dercon and Christiaensen, 2011; Jensen, Barrett, and Mude, 2017; Janzen and Carter, 2019), improve household income through farm revenue or livestock productivity (Karlan et al., 2014; Jensen, Barrett, and Mude, 2017), and improve subjective welfare of the insured households (Tafere, Barrett, and Lentz, 2019). This paper adds to evidence showing that children also benefit from microinsurance.

Our findings add evidence to the literature on the effect of insurance on child labor and education. The existing literature finds that the decreased uncertainty should decrease child labor and increase child schooling (Beegle, Dehejia, and Gatti, 2006; Pouliot, 2006; Landmann and Frölich, 2015). However, studies on the relationship between a household's productive assets and child labor show that increased productive assets could increase child labor (Basu, Das, and Dutta, 2010; Edmonds and Theoharides, 2020). Exploiting a unique setting where insurance could induce both forces, this paper shows how a household decides under such settings.

Both of these two contributions have relevance to social policy. First, microinsurance is a social protection policy feasible in low- and middle-income countries that recently received growing attention. This paper highlights that microinsurance could contribute to long-term economic development by inducing human capital accumulation among insured households.

Moreover, the results of this paper have relevance for the child labor policy as well. Child labor reduction policy has focused on supporting household income. In the same vein, the effectiveness of poverty graduation programs such as asset transfer programs received increasing attention. Purchasing insurance with subsidy enhances certainty in income from productive assets. This paper shows that instead of directly increasing the productive assets, increased certainty could allow households to make longer-term investments, such as investment in children's human capital.

The paper proceeds as follows. Section 2 discusses a conceptual framework. Section 3 explains the study settings, and Section 4 describes the dataset and Section 5.1 the empirical strategy used for the estimation. We present the estimated results in section 6 and conclude in Section 7.

2 Conceptual Framework

The effect of microinsurance on child labor is ambiguous analytically. A pastoralist household produces livestock-related products such as milk, meat, or traded livestock. Inputs used to produce these outputs include labor, fodder, and livestock. Here, livestock works as a capital, which is a source of input and works as an asset. Labor input consists of adult and child labor, where adult labor is inelastic. Unlike adults who spend their time on work and leisure only, children allocate their time among work, schooling, and leisure. Children's investment of their time in schooling will increase the household budget of the future periods, thereby increasing the sum present value of the household utility.

The household enjoys its utility from consumption and leisure. Since both the credit and labor markets are not complete, the production decisions are not separable from the consumption decisions. Therefore, children's work increases utility by increasing the household budget through production but decreases utility by decreasing leisure hours and schooling investments.

Children in pastoral households are likely to be involved in livestock-related work. Male children, when they become a certain age, start participating in herding the animals. Other children are also engaged in livestock-related tasks such as feeding the animals kept at the main basecamp, milking the lactating animals, or selling livestock-produced goods.

Since the labor market for children is close to nonexistent, children's work is restricted to within-household tasks. Thus, as the herd size increases, demand for children's engagement in work will grow. However, the wealthiest households who could afford hiring herders may choose to employ herders instead of sending children to work.

A large and important part of herding activity is to take the livestock to grazing land where animals can feed. Herd mobility is an important herding strategy both in the long term and in the short term. In the long-term, it maintains the grazing land condition at a sustainable level. In the short-term, mobility increases the quantity of the animal feeding (Hurst et al., 2012). Drought in the area induces more households to choose to become transhumant to feed their animals.

IBLI insures the livestock loss due to droughts in the area. Therefore, it affects multiple aspects of pastralists' livelihood, including herding strategies, herd size, and, the income from livestock rearing. With this in mind, we can hypothesize the direction of the effects from IBLI on children's activity status.

First, the IBLI can influence children's work and schooling status directly. If child labor is a form of self-insurance of a household, uninsured risk exposure causes welfare losses that induce more child labor. IBLI protects pastoralists from using destructive risk mitigation strategies such as distress sales and consumption reduction upon drought shocks (Jensen, Barrett, and Mude, 2017; Janzen and Carter, 2019). Based on the existing evidence showing that uncertainty in productivity and child labor are negatively correlated (Pouliot, 2006; Landmann and Frölich, 2015), reducing uninsured risk exposure through programs such as IBLI may cause welfare gains and decrease labor allocations toward children.

As shown in Karlan et al. (2014), agricultural insurance could substitute away the use of hedging input while increasing the use of risky input. Labor input is considered as a risky input since it has higher marginal productivity in the good season compared to the bad season, by definition. Similarly, children's work is likely to be considered as a risky input, so the insurance could increase the use of children's labor.

IBLI indirectly changes children's work and schooling status. Since child labor is complementary to livestock holdings, it will change depending on the changes in livestock holdings and herding strategies of the pastoral households. For example, a household could use IBLI to replace livestock savings as an inefficient means of insuring against a drought risk. Then the herd size would decrease, and so would child labor.

However, microinsurance could also increase a child's participation in work. IBLI protects non-poor households from asset decumulation (Chantarat et al., 2013) and increases productivity-enhancing investment (Jensen, Barrett, and Mude, 2017). In other words, IBLI could increase the risk-adjusted returns to livestock holding. Basu, Das, and Dutta (2010) and Edmonds and Theoharides (2020) showed that the increase in a household's productive asset could increase demand for child labor. The herd growth relevant to the increased return in livestock holding will stimulate an increase in child labor.

IBLI could also work through income. It increases income per adult equivalent[1], as found in Jensen, Barrett, and Mude (2017). By findings from a canonical model of Basu and Van (1998) and subsequent studies on the determinants of child labor, we expect that the positive income effect will decrease children's work (Edmonds and Schady, 2012; Edmonds, 2008).

Therefore, the effect of livestock insurance on child labor use is an empirical question to be addressed. A piece of evidence on the effect of IBLI on child outcome suggested that the effects are small. The effects on school absenteeism were small and statistically insignificant (Jensen, Barrett, and Mude, 2017).

3 Study Settings

3.1 Marsabit and Borena

Marsabit district of Kenya and Borena zone of Ethiopia are two areas bordering each other, as depicted in Figure 1. Geographical proximity comes with being in the same agroecological zone. They are both Arid and Semi-Arid Lands(ASALs), where pastoral livelihood systems are dominant. Within our sample, 87 percent of the households have at least one household member doing livestock-related work. Previous studies demonstrated that poverty traps exist in these pastoralist economies, and droughts are the key exogenous driver of the poverty traps (Lybbert et al., 2004; Santos and Barrett, 2011). Furthermore, climate change increased the frequency of droughts and will lead to a risk system collapse in the absence of interventions to enable faster herd recovery from drought-related losses (Barrett and Santos, 2014).

Educational attainment in these areas is lower than that of the other areas. In Kenya, the population share without any education is 54 percent in the Marsabit district, while only 10 percent in other regions. Similarly, in Ethiopia, the population share without any education is 70 percent in the Borena zone, while 39 percent in other regions. For children aged 5 to 17, 37 percent have never received any education in the Marsabit district, while 13 percent in other regions. [2] On the

[1] An adult equivalent is defined as follows, where age is in years. AE=0.5 if age < 5, AE=0.7 if $4 <$ age < 16 or age > 60, AE=1 if $15 <$ age < 61.

[2] These numbers are calculated by the author using the publicly available household survey. We use Kenya Inte-

supply side, It is challenging to deliver quality education and attract qualified teachers to these areas due to the scattered population and remoteness of villages and seasonal and periodic movements of pastoral communities. Governments of both countries are aware of and have made efforts to address the situation. To increase the accessibility of education, governments provide alternative platforms to deliver education to children from pastoralist society, such as mobile schools and Alternative Basic Education (ABE) for lower-level primary education.

However, education curriculum and language of instruction have had very little significance to pastoralist and nomadic populations (Ruto, Ongwenyi, and Mugo, 2009). Since mobility is crucial in pastoral livelihood, a formal school system requiring the students to be sedentarized at one place for a while is hardly productive. Moreover, spending time away from their family and not learning productive animal production skills may not be considered as a better way to spend a child's time. Figure A1 shows that the demand side issue seems to be more prominent in these regions. In the Marsabit district of Kenya, the two major reasons children never enrolled in school are parents' refusal to send their children to school and work burden at home, while the age restriction is a major issue in other areas along with parents' refusal and costs. However, the supply side reasons such as low school quality or a distance to the schools do not seem to be the reasons for children's low school enrollment in the Marsabit district. Similarly, in Ethiopia, work and parents' perception of education are the two major reasons, along with the age restriction, why children never enrolled in school across regions. Again, the supply-side issue does not seem to consist large portion of the reasons.

The value of child labor is high in pastoralist households. Both male and female children in a pastoralist household are important labor forces for the family's livelihood. In Kenya, 13 percent of children are engaged in any economic activity. The number does not include any help in household tasks. However, more children – 19 percent of children – are engaged in economic activities in the Marsabit district. Moreover, 97 percent of these children engaged in economic activities from the Marsabit district responded that their primary or secondary activity is pastoralist activities. These working children from the Marsabit district work for strikingly long hours. Children of 5 to 17 years old from the Marsabit district work 68 hours per week, while children from other parts of Kenya work only 20 hours on average (Data from Kenya Integrated Household Budget Survey 2015-2016)[3]. Child labor is prevalent in the Borena zone of Ethiopia as well. While 27 percent of Ethiopian children are engaged in economic activities on average, 56 percent of Borena zone children work. Moreover, these children work for 31 hours per week, compared to 23 hours among

grated Household Budget Survey 2015-2016 was for Kenya and Socioeconomic Survey 2015-2016 for Ethiopia.

[3]Working hours are measured by asking the usual hours of work for any economic activities that children are engaged in. However, the numbers are similar when the working hours are measured by the sum of actual working hours in the last seven days for a child's primary and secondary activities.

children from another area (Data from Socioeconomic Survey 2015-2016). While the weekly working hours differ across countries due to measurement methods, it demonstrates that children in our study areas work more intensely than the other parts of the country.

A higher intensity of child labor in our study areas is related to the fact that most households in our study area are pastoralists. Within our sample, 70 percent of children aged 5 to 17 participated in work, and 61 percent were engaged in livestock-related activities. The relationship between children's activities and herd size depicted in Figure 3 demonstrates the importance of child labor in livestock production. It plots the distribution of livestock at the child level, along with the probability of children's work engagement (Panel A) and hours of work each child participates (Panel B).[4] The distribution at the household level looks similar, which we present in the Appendix. Panel A shows that the probability of a child's full-time engagement in work increases as the herd size grows, while the probability of child work and going to school decreases, and the probability of school enrollment stays relatively constant. Notably, the children from households with the smallest herd sizes choose to work and go to school simultaneously more than they work full-time. The intensive margin presented in Panel B shows that the daily working hours also increase with the herd size, while hours spent on schooling and adults' working hours are relatively similar across herd sizes.[5] Moreover, the number of hours that adult household members work on average, plotted in black line, is constant across the distribution of herd size. Again, children from households with smaller herd sizes spent more time on schooling than on work. It shows that the less wealthy households seem to be investing more in children's schooling, contrasting a usual expectation.

A working environment in livestock herding bears the risk for children. There exists dangers from cattle and wildlife, as well as animal-bourne diseases. The fact that wealthier households who can choose to enroll their children in school put them in work despite these conditions suggests that the relative net benefit of going to school is lower than working.

3.2 Index Based Livestock Insurance

Index-based livestock insurance (IBLI) is designed to cushion households against drought-related losses to accelerate recovery from shocks, build households' resilience to drought, and avert collapses into poverty traps (Chantarat et al., 2013). The IBLI product description in this section is largely drawn upon from Jensen, Barrett, and Mude (2017) and Janzen and Carter (2019).

As index-based insurance, the indemnity payout is triggered if an index of the insurance area

[4]Here, working hours are conditional on a child working.

[5]Tropical Livestock Unit (TLU) is an integrated unit for cattle, camel, sheep, and goats. TLU allows us to measure the number of different types of livestock in one unit. 1 TLU = 0.7 Camel = 1 Cattle = 10 Sheep/goats

satisfies a certain threshold. The predicted livestock mortality is used as a criterion for payout decisions. In Kenya, the predicted livestock mortality rate higher than 15 percent triggers the indemnity payout, while the forage condition index ranked at 15th percentile or higher on the historical distribution at the Woreda-level since 1981 is used as a threshold in Ethiopia. Normalized Differenced Vegetation Index (NDVI) and longitudinal household data on livestock mortality rates are used to construct the average predicted livestock mortality rates in both countries. Chantarat et al. (2013) provides analytical detail about the modeling process. The index was computed at a sub-location level. For example, Kenya's Marsabit district was divided into five insurance divisions while the Borena Zone of Ethiopia into eight Woredas. This way, the index better reflects the systematic differences in rangeland and climate conditions across areas.

By using NDVI – a measure collected by an external organization at the area-aggregate level, the IBLI does not incur the cost of verifying individual loss claims and reduces the problems of household-level adverse selection and moral hazards. Moreover, using the combination of NDVI index and household data allowed IBLI to minimize the expected basis risk, which is a problem for index insurance in general. The demand for IBLI products within the study sample of Kenya was 40 percent (Jensen, Barrett, and Mude, 2017), which is a moderately high level of demand but much higher compared to other index-based microinsurance products.

There are two seasons in the study areas. Long-Rain, Long-Dry (LRLD) season spans from March to September, and Short-Rain, Short-Dry (SRSD) season from October to February of the following year, as depicted in Figure 2. IBLI sales windows were two months preceding the two rainy seasons – January to February and August to September. The coverage periods lasted for one year for insurance, so if a household purchases insurance in two consecutive seasons, there will be a period with overlapping insurance coverage. Policies are sold in Tropical Livestock Units (TLUs), and the premiums were calculated by the product of premium rate, insured livestock in TLU, and the price per TLU. The local insurance companies that pastoralists are familiar with sold insurance products in both countries. There were two payouts triggered in Marsabit, Kenya, in 2011 and 2012 while one in 2014 in Borena, Ethiopia (marked in yellow bar in Figure 2. Considering payouts are triggered only when a drought happened in the insurance area, there were five incidents of droughts in northern Kenya and one in southern Ethiopia during our sample periods.

The International Livestock Research Institute (ILRI) and a team of researchers implemented evaluation pilot programs using various interventions to raise awareness of and demand for the product in the study area. The programs were implemented from 2009 to 2015 in Kenya and from 2012 to 2015 in Ethiopia. Interventions included recorded tapes and cartoons with information on IBLI products (Borena), IBLI knowledge games (Marsabit), and discount coupons. The discount coupons were randomly distributed to the subsample of the households in each insurance area in each round. In other words, the randomization for the coupon receiving households was administered every round – so a control group in one season may become a treatment group in another season. The discount was applied to the first 15 TLUs insured, and the rate of discount ranges from 10 to 60 percent in Kenya and 10 to 100 percent in Ethiopia, at 10 percent intervals. Note that in rounds 5 and 6, some Kenyan participants also received a 70 to 80 percent discount. As depicted in Figure 5(a), 60 percent of the total sample received discount coupons in Kenya while the remaining 40 percent did not. In Ethiopia, 80 percent of the sample received coupons. The discount could be significant. The premium for the 15 TLUs could range from 8,285 to 16,575 ETB (equivalent to USD 466 to 932) in Ethiopia, and 5,850 to 24,600 KSh (equivalent to 74 to 280 USD) in Kenya. Figure 5(b) shows that most households insured less than 15 TLU even with the discount, since it was a significant amount for the poor households in these countries.

4 Data

This paper uses two main data sources. The first source is data from a household panel survey conducted by the International Livestock Research Institute (ILRI) and Cornell University. The survey was conducted in an effort for continuous impact evaluation and assessment of the IBLI product. It was conducted as part of the pilot program described in the previous section, so the survey collects information on households living in the Marsabit district of Kenya and the Borena zone of Ethiopia. The survey collected information at baseline and followed the households annually. In Marsabit district, the baseline survey was conducted in 2009 and 2012 in Ethiopia. In the Marsabit district, 924 households were interviewed at baseline, while 528 were in the Borena zone. The survey collected comprehensive information on households' living standards and herding practices, child participation, and hours spent working and schooling. Another data source is the insurance company's administrative data, which includes the information on the households' purchase of insurance and the distribution of the discount coupons.

The focus of this paper is the effect of microinsurance on child labor and schooling. To evaluate this, we measure the work and schooling of a child in the following way. A child is defined to work full-time if both primary and secondary activity of a child over the last 12 months is recorded as work. Work includes a wide range of activities, including herding livestock, livestock production, working in small businesses, casual labor, and household tasks.[6] We also use a measure of a child's

[6]List of activities classified as work: Herding (household-owned) livestock, livestock production (e.g., milking, sale of livestock products), livestock trading/broker, petty trading (e.g., charcoal/water trading), shop/business owner, unpaid work in family's shop/business, casual labor (e.g., herding for pay), wage/salaried employment, farming (non-livestock), house/domestic work, fishing, poultry production, mining.

work – criteria used by UNICEF to define child labor to complement the mutually exclusive four categories of activities. According to this definition, a child is classified as doing child labor if i) a child of age 5 to 11 years is engaged in at least 1 hour of economic work or 21 hours of unpaid household services per week, ii) a child of age 12 to 14 years in at least 14 hours of economic work or 21 hours of unpaid household services per week, or iii) a child of age 15 to 17 years in at least 43 hours of economic work per week. A child is doing part-time work and schooling if a child reports that one of his/her primary or secondary activities is work and the other is to be a student. Full-time schooling means that a child reported that his/her primary or secondary activity is a student, while the other is unanswered or no activity. Lastly, we define a child as "No activity" if he/she falls into neither of the three previous categories. Full-time work, part-time work and schooling, full-time schooling, and no activity are exhaustive and mutually exclusive categories of children's activity, while child labor is not. Another set of main outcome variables is the hours spent on activities. Hours spent on each activity in an average day were collected, so this information is used. We subtract hours spent on work and schooling from 24 hours to compute hours spent on neither work nor schooling. We also use school enrollment, years of education, dropout, and grade progression as another set of outcome variables to verify the result. Here, a student is defined as enrolled in school if he/she was enrolled in school in the last 12 months.

Herd size and age are important factors determining children's activity. Figure 3 shows that the distribution of the herd size owned by each household is right-skewed. Most households own a herd size smaller than 40 TLU, and the households with a herd size larger than 60 TLU are rare. The figure also shows that the probability of working full-time increases as the herd size increases, while the probability of part-time work and schooling decreases.

We restrict our sample to children aged 5 to 17 for our analysis for several reasons. First, it is common in the literature on child labor to study children aged 5 to 17. Secondly, we consider the two country's minimum legal working age. Ethiopia's minimum legal working age was 14 before, and it changed to 15 in 2019 and 18 for hazardous work. In Kenya, the minimum legal working age to work is 17 and 18 for hazardous work. Therefore, we use 17 years old as the upper bound of the age to restrict the sample. Figure 4 shows the probability of a child working at each age by gender. It shows that 40 percent of children either work or study at age five, and almost 60 percent are involved in no activities. This probability drops to almost 0 by the age of ten, and most children participate in work or school. One notable difference between genders is that boys are more likely to be working full-time at all ages, while girls are more likely to be going to school and working at the same time between the age of 8 and 15.

5 Empirical Strategy

5.1 The Effect of Insurance

We investigate the impacts of microinsurance on child outcomes and its mechanisms. The most straightforward study design would be to exploit an exogenous variation of household insurance coverage and compare the group of uninsured and insured households. However, as stated in Section 3.2, all households within our sample had access to the insurance. The purchase of the insurance is thus inherently endogenous, and we have to deal with the selection into the insurance coverage. Jensen, Mude, and Barrett (2018) shows that the demand for the IBLI product is driven by basis risk, participation in social groups, price of the insurance, financial liquidity, and adverse selection in Kenya. Financial liquidity, for example, is also correlated with child work and schooling. To address the selection issue, we instrument insurance coverage with a premium discount provided by randomly distributed coupons, following Jensen, Barrett, and Mude (2017).

As the first stage, we estimate:

$$CIBLI_{hrt} = \gamma_0 + \gamma_1 DC_{hrt} + X'_{iht} \cdot \gamma_2 + \delta_h + \theta_t + \psi_r + \eta_{hrt} \quad (1)$$

where $CIBLI_{hrt}$ denotes the cumulative insurance takeup of the household h in region r covering the period t, and $DChrt$ denotes the cumulative discount rate over the same sales seasons. Insurance takeup can be measured by the insurance uptake and the coverage in Tropical Livestock Units (TLU). Since the discount rates predict insurance uptake stronger than the coverage in TLU, our preferred specification is the one using the insurance uptake. Cumulative insurance takeup is the total number of insurance takeup incidence over the three consecutive sales seasons prior to the survey. Insurance coverage spans for one year, and there are two sales periods in each round. The child outcome measures a child's primary activity during the 12-month period preceding the interview. Figure 2 shows that there could be up to three relevant IBLI sales periods that could affect a household's child labor decision. Therefore, $CIBLI_{hrt}$ denotes the total number of insurance uptakes over the three recent sales season, and $DChrt$ denotes the cumulative discount rate over the same sales seasons.[7] Figure A2 presents the distribution of cumulative discount rates and insurance takeup over the one year period. On average, the coupon recipients were provided with 63 percent discount rates, and 26 percent of the households purchased at least once in the period of a year.

Household-level characteristics that are time-varying, X'_{hrt}, are included, as well as household-,

[7]For example, in round 3 of Ethiopia, August-September 2012 sales season, January-February 2013 sales season and as August-September 2013 sales season are relevant.

time-, and region- fixed effects to control for time-invariant household characteristics, common time trends across regions, and region-specific characteristics. η_{hrt} denotes the error term, clustered at the household level. The error term is clustered at the household level to allow for intra-household correlations.

Using the predicted values from the Equation (1), we estimate the following second-stage regression equation:

$$y_{(i)hrt} = \beta_0 + \beta_1 CIB\hat{L}I_{hrt} + X'_{(i)hrt}\beta_2 + \delta_{iorh} + \theta_t + \psi_r + \varepsilon_{(i)hrt} \tag{2}$$

where y_{ihrt} is the outcome of child i in household h living in region r at period t. Other notations are the same as used in the previous equation. For some of the outcome variables measured at the household level, we collapse the dataset at the household level and estimate the regression. Household-level outcomes include size of the livestock that the households own, herd, that are adults, at home, and lactating at the time of the survey. Since the unit of the randomization was at the household level, the effects on individual-level outcomes may be weighted by the number of children in the household. Therefore, we weight the regressions by the number of children in households for the analysis of child outcomes. These include indicators for the probability of and hours spent on child work (full-time and part-time), schooling (full-time), and no activity. These four categories are exhaustive and mutually exclusive. β_1 is the coefficient of interest, which captures the average effect of insurance on children's activity status.

5.2 The Effect of Insurance upon shock

During our study period, droughts occurred in two sales seasons in Marsabit and one in Borena. Using this information, we also estimate the effect of insurance when the drought shock hits the region. As the first stage, we estimate:

$$CIBLI_{hrt} = \gamma_0 + \gamma_1 Shock_{rt} + \gamma_2 DC_{hrt} + \gamma_3 Shock \cdot DC_{hrt} + X'_{iht} \cdot \gamma_4 + \delta_h + \theta_t + \psi_r + \eta_{hrt} \tag{3}$$

where all variables share the same definition as in Equation (1) except for $Shock_{rt}$, which is an indicator equals one if the region r experienced drought shock in period t. Here, period t is 12 months period before the interview. Note that the recall period for the child outcome is 12 months before the survey, but the drought shock was measured at the end of each agricultural season, so it was computed twice per year. Moreover, payouts were triggered after each agricultural season. Therefore, our estimates in this regression capture the effect of insurance on outcome variables as a mixture of ex-ante and ex-post risk-coping strategies. For example, survey round 4 in the

Borena zone collects information on child outcomes from the period of March 2014 to February 2015. Since there was a payout in November 2014, it means that some regions experienced drought shock in Long-Rain, Long-Dry season of 2014. Hence, our estimates of the insurance effect on child outcome capture the average of the household's response to the shock and to the payouts.

Since we are interested in the differential response across insured and uninsured households upon shock, we use two endogenous variables: The insurance takeup dummy and an interaction of the insurance takeup dummy and the drought shock dummy.

Using the predicted values from the Equation (3), we estimate the following second-stage regression equation:

$$y_{(i)hrt} = \beta_0 + \beta_1 Shock_{rt} + \beta_2 CIB\hat{L}I_{hrt} + \beta_3 Shock_{rt} \hat{\cdot} CIBLI_{hrt} + X'_{(i)hrt}\beta_4 + \delta_{i,orh} + \theta_t + \psi_r + \varepsilon_{(i)hrt} \tag{4}$$

where $CIB\hat{L}I_{hrt}$ is the predicted value from Equation 3. Here, β_1 captures the effect of drought shock on households without any insurance coverage, and β_2 captures the effect of insurance uptake on activities of children from households with livestock insurance coverage. β_3, on the other hand, captures the difference between the children from insured and uninsured households upon drought shock. Therefore, whether the insurance protects households from the drought shock can be estimated by the sum of β_2+β_4, which we present at the bottom of each table separately.

5.3 Validity of the instruments

Instruments are valid when the two following assumptions are satisfied: i) independence of the instrument and ii) exclusion restriction. Since our instrument is from the randomized encouragement design, it should not correlate with any observed and unobserved heterogeneity in principle. To ensure the random distribution of the coupon, we test the balance of demographic characteristics between households that received and did not receive coupons. Table 1 presents the summary statistics and the mean difference of the variables between coupon recipients and non-recipients. We present both the mean-difference of these sets of variables and the p-value of the joint orthogonality test of the variables to the coupon distribution to show that the two groups do not differ in observables. Presenting these two complementary measures is necessary since the local insurance company did the distribution of the coupons, and there were differences in the actual distribution and what the research team had planned. We use administrative records of discount coupon distributions and insurance purchases to avoid the concern about this non-compliance and check the potential imbalance of the characteristics.

Exclusion restriction requires the instrument to be correlated with endogenous variables while not correlated with the unobserved heterogeneity, denoted by ε_{ihrt}. We cannot empirically show this, but it is reasonable to assume that the randomized discount coupon offers to affect households' decision on child time allocation only through insurance uptake decisions.

Another concern about the instrumental variables approach would be the issue of weak instruments. Table 2 shows the result from the first stage estimation – Equation 3 and 1. Columns (1) and (2) show the correlation between the two endogenous variables and the two instruments employed in Equation 3. The results show that the cumulative coupon discount rate in non-drought periods strongly predicts the cumulative insurance uptake in the non-drought periods. The cumulative discount rates in the drought period strongly predict the cumulative insurance uptake in the drought period. Column (3) and (4) present the correlation coefficients from estimating Equation 1. While Column (3) presents the coefficients using cumulative insurance uptake and discount rate among the three latest sales seasons. The estimated coefficients are positive and statistically significant at the 1 percent level, suggesting strong predictive power at the first stage.

First stage F-statistics jointly testing all coefficients of the first stage regression equals to zero is commonly used to argue that the instruments are not weak. Under heteroskedastic error, the effective first-stage F-statistic of Montiel Olea and Plueger (2013) is commonly used to test the weak instrument problem. This method can be used when there is one endogenous variable since calculating effective F-statistic under two endogenous variables is yet to be developed. We present these effective F-stats (denoted by F_{eff}) at the bottom of the tables whenever possible. In the case of the coefficients for Equation 4, technically there are two endogenous variables, but since $Shock_{rt}$ is exogenous to the local economic conditions, including the interaction of $Shock_{rt}$ and $CIBLI_{hrt}$ should not constrain the predictive power at the first stage. We present Kleibergen-Paap rk Wald F-statistic, as a complementary measure of a first stage predictive power. We present the p-value of the Anderson and Rubin test as well. While the p-value does not test the weakness of the first stage estimates, it assures that the second stage estimate is robust to the case of multiple endogenous variables. We find that in all cases where the estimates are statistically significant, AR p-value is also below 0.05.

6 Results

6.1 Effects of insurance takeup on children's activity choices

We first examine the average effect of insurance. The results presented in Panel A of Table 3 show that on average, the insurance shifts children's activity from part-time work to full-time schooling. We find that the insurance take-up over the past year decreases the probability of children's work. For an additional insurance take-up experience over the three past seasons, the probability of child labor decreased by 8.5 percentage points, and part-time work and schooling by 10.1 percentage points. These estimates are statistically significant at five and one percent levels, respectively. The effects are large in magnitude. Compared to the mean of the outcome variables of the non-coupon recipients, child labor decreased by 20 percent, and part-time work and schooling by 40 percent. The average insurance take-up rate covering one year is about 32 percent. Thus the actual effect is smaller, but there is a substantial decrease in children's work. Moreover, the probability of full-time schooling increases by 12.2 percentage points, statistically significant at a 1 percent level. On the other hand, the effect on the probability of working full-time is estimated to be -0.02, and the probability of participating in none of the activities is estimated to be 0.04, but the coefficient is not statistically significant. Effective F-statistics are larger than the 5 percent critical value for all specifications, indicating a low probability of weak instrument.

We disaggregate the average effect to the effects during the drought and non-drought periods. The estimated impact presented in Panel B of Table 3 reveals that the average insurance effect shifting children's part-time work to full-time schooling was driven by the effects in non-shock periods, and children are drawn to work more when the drought occurs without insurance, but the insurance protects children from this. First, the estimates presented in the second row of each panel show results consistent with that of Table 3, showing that children from the insured households decrease part-time work and schooling and increase full-time schooling. However, the average negative effects on child labor are not driven by the effects in non-shock periods. The coefficient on child labor is negative but small in magnitude and statistically insignificant.

Next, the coefficients on *Shock* show that households with no insurance increase child labor upon droughts by 9.6 percentage points. It is 18 percent increase, which is large in magnitude. However, the insurance offsets the increase in child labor – the coefficient on $Shock \times Uptake$ is -0.180, statistically significant at 10 percent level. As a result, the effects on the children from insured households during drought shock are indistinguishable from zero, as shown by the sum of the two coefficients. Other activities do not change substantially during the shock periods even without insurance, and we can reconcile this result using the effects on children's working hours presented in Table A2. It shows that working children increase hours spent on work upon shock without insurance, supporting our finding on child labor.

To complement the lack of appropriate 1st stage F-statistics and ensure that our estimates are not threatened by the weakness of the first stage estimates, we repeat the estimation in Table **??** using a single endogenous variable and present the results in A1 with effective F-statistic. Panel A shows that the cumulative insurance uptake indicator does not suffer from a weak instrument problem since the effective F-statistic is higher than the 5 percent critical value threshold for all models. While the effective F-statistic presented in Panel B is smaller than the 10 percent critical value, it is due to mechanical reasons. Since the interaction term suppresses the insurance take-up decisions in non-shock periods, the set of exogenous variables – cumulative discount rate and its interaction with the shock period – naturally have weaker predictive power for the endogenous variable. However, since we showed that the predictive power is strong enough for the endogenous variable without the interaction with the shock indicator, we confidently present that the estimates do not suffer from the weak instrument problem.

Using how the activities were classified, we examined which type of activity is the driver of the decrease in children's work participation. The survey asked the child's primary and secondary activity over the last 12 months and which type of work children participated in. The results presented in Panel A of table 4 shows the average effect of the shift from part-time work and schooling to full-time schooling is driven by the children reducing work as a secondary activity by 12.1 percentage points. Consistently, insurance uptake increases schooling as a secondary activity. Considering only 2.5 percent of the children working part-time and going to school responded that they go to school as their primary activity and work as a side, the decrease in work as a secondary activity is consistent with the shift from part-time work and schooling to full-time schooling. However, we cannot reject that the insurance uptake did not affect the work as a primary activity. The coefficients of $Update$ on these variables in Panel B also support our previous finding of the effects from the non-shock periods.

We find additional supporting evidence of children increasing work participation upon drought shock by examining livestock-related activities. [8] The results in Panel B show that children from uninsured households' participation in livestock-related work as their primary activity increases in drought periods. These children are 5.6 percentage points more likely to be engaged in livestock-related work as their primary activity, estimated at a 5 percent statistical significance level. We confirm that the children from insured households, on the other hand, do not experience an increase

[8] For example, herding (household-owned) livestock, livestock production such as milking, sale of livestock products, livestock trading/broker are included in this category. Among four types of livestock-related tasks, herding household-owned livestock consists of the highest portion.

in livestock-related work participation.

6.2 Potential Mechanisms

In the previous subsection, our empirical analysis revealed two things about the effect of IBLI: a) On average, it shifts children from part-time work and schooling to full-time schooling, b) Upon shock, households increase children's engagement in livestock-related work as children's primary activities, but insurance offsets this effect. To understand the mechanism behind these findings, we start by examining the effects on livestock holding. IBLI could have indirect effects on households' child labor choices by affecting the size of the livestock holding of the households, so the demand for child labor to take care of the livestock could change accordingly. Since effects during the non-shock periods drive the average effects are driven, we examine the disaggregated effects in this subsection. Relevant average effects are reported in the Appendix.

Mobility is an important herding strategy for households and affects the demand for children's work and schooling. We measure mobility in two ways; whether a household is partially or fully mobile and the share of livestock holdings kept away from home. The two measures are positively correlated but highlight different aspects of herding behavior. While the indicator for a fully sedentary household focuses on whether a household is mobile, the share of at-home livestock is the intensity of the mobility. Columns (1) and (2) of Table 5 show that both measures increased during the non-shock period, suggesting that the households are more likely to be mobile. It explains the shift from part-time work and schooling to full-time schooling during the non-shock period and on average. As explained previously, most of the children who are participating in work and schooling simultaneously choose schooling as a primary activity and work as a secondary activity. When a household chooses to increase the mobility of the herd, which requires staying at satellite camps for usually a month, children previously engaged in work as their secondary activity drop work instead of dropping out of school, thus increasing the probability of full-time schooling.

Diversification is another strategy that households can choose to mitigate drought risk. We measure diversification in two ways - the number of livestock types and the number of income sources. The number of livestock types ranges from zero to three, and it shows within livestock diversification. The number of income sources shows the degree of livelihood diversification. We find that both measures show no substantial changes in livelihood diversification.

In addition, we also observe an increase in livestock-related expenditure during the non-shock periods. Table 6 shows that while expenditures on food and non-food items are not substantially affected by the insurance in any period, the livestock-related expenditure, especially expenditure on livestock food (e.g., water, fodder, and supplementary feeding for livestock), increases during the non-shock periods. It suggests that the pastoralists increase investments in risky input during non-shock periods since the livestock food will have higher marginal returns during the good season (non-shock season), which we do not find in the results on children's work and schooling. The fact that we do not find an increase in children's engagement in livestock-related work during the non-shock periods despite this increase in investments on risky input shows that the changes in herding strategies and the increased cost of hiring children in that setting dominates the incentives to invest in risky inputs such as children's work.

Another potential channel is livestock holding. Estimates presented in Table 7 provide evidence on the mechanism of the second finding, where the insurance protects children from being drawn to work more. The estimates show that uninsured households increase their livestock holding when the drought shocks occur, and the insurance offsets this. The effects are similar to the case for owned livestock, herding livestock, adult animals, and lactating animals. We also find similar effects on the milk sales of the pastoral households, while milk production does not move in the same way. The result is consistent with the pattern found in children's livestock-related work as a primary activity. We further examine to reconcile the finding that livestock holding increases upon drought shock without insurance. To do this, we examined the heterogeneous effects of shock and insurance across initial herd sizes: We divided the sample into quartiles using the herd size at baseline and estimated the effects within each group. The result presented in Table 8 shows that the increase in herd size is driven by the households from the top half of the distribution. It indicates that the households with larger herd size at baseline increase herd size upon drought to use the arbitrage. Therefore, a plausible story is that households with larger herd sizes increase livestock holdings during droughts, which leads to demand for labor in livestock-related work within the household, increasing child labor. However, the insured households face weaker incentives to exploit the opportunity since the insurance claim can pay off their loss. Therefore, no substantial changes in the engagement in livestock-related work of children from insured households.

These results on potential channels do not pinpoint the mechanism through which microinsurance affects children's work and schooling. However, they reveal conditions under which specific effects can dominate the others. For example, when the drought shock occurs, increased livestock holding of households induces an increase in children's work in livestock-related tasks, but the insurance substitutes this need. It substitutes children's work as a buffer stock. The average shift from part-time work and schooling to full-time schooling seems to be driven by the increased mobility of the households. Increased mobility increases the cost of accessing school, inducing children to drop the work as a secondary activity and focus on schooling (if they were working primarily). Also, there is suggestive evidence of increased investment in risky input, but children's work and schooling status do not follow that pattern.

6.3 Heterogeneity of the Effects

We examine the heterogeneity of the effects by households' demographic characteristics such as age, birth order, and gender. Panel A of Table 9 shows that the effects are not statistically different between the younger age group (5-12 years old) and older age group (13-17 years old). If anything, both age groups increase full-time schooling, but younger age group children do not decrease the full-time or part-time work. It may suggest that older children benefit more from insurance on average. However, the magnitude of these effects is larger for the older children, and the increase in full-time schooling of older children almost entirely comes from a decrease in part-time work and schooling. Likely, children who were already going to school stop participating in work and attempt to focus on schooling, rather than the households decide to enroll a new batch of children who were not enrolled previously. On the other hand, an increase in full-time schooling of younger children can be explained by a decrease in both full-time works (although not statistically significant) and part-time work and schooling. Younger children decrease child labor as well, which is an indicator of a decrease in heavier workload. Moreover, Panel B presents suggestive evidence showing that the older age group children experience heavier workload, especially upon shock. When a household is not insured, the older children increase work as primary activities and decrease full-time schooling.

A similar but more evident pattern arises in the heterogeneity by birth order presented in Table 10. We find that all children increase participation in full-time schooling here on average. However, the oldest sibling decreases part-time work and schooling while the younger ones decrease full-time work participation and child labor. The difference in these variables across the two groups is statistically significant. Moreover, while the oldest child decreases doing household tasks, younger siblings decrease participation in livestock work. Similar to the heterogeneous effect by the age group, it is the oldest sibling who bears the increased workload upon the drought shock.

The effects were statistically similar between genders in general. Table 11 shows that both genders switched from part-time work and schooling to full-time schooling. However, a decrease in child labor of girls was statistically significant at 5 percent level while it was small and not statistically significant among boys. The results suggest that the households prioritized decreasing girls' participation in more severe forms of work than in boys. However, it does not lead to an increase in girls' full-time schooling disproportionately. Panel B explains this inconsistency. Panel B shows that the households increase girls' participation in work activities and decrease girls' schooling upon drought shock. It may reflect that the boys are more likely to participate in economic activities already, but it also reflects the existence of gender disparity in work and education.

6.4 Robustness check

We ensure our results are robust to various specifications. First, Jensen, Barrett, and Mude (2017) points out that the effect of lapsed insurance may accumulate towards the future to affect the behaviors of the households. Therefore, they analyzed the effect of current and past insurance purchases simultaneously. In our specification, the cumulative IBLI take-up measures the number of IBLI take-up over the three latest sales seasons due to the recall period of child outcomes. Therefore past purchases in our case must have happened at least four sales seasons ago, and the lagged effect of past purchases from a long time ago may have dissipated. It is still possible that these longer-term lagged effects survived, so we show the estimates, including the cumulative past insurance take-up as a second endogenous variable. In this case, we cannot adequately test for the weaknesses of the instrument, so we focus on the estimated results. Table A7 shows that our results are robust to the inclusion of the past insurance purchases.

Another set of results uses the insurance coverage as an endogenous variable instead of the insurance take-up, measured by Tropical Livestock Units. Table A8 shows the results are robust to a different measure of insurance coverage. Our preferred specification is the number of incidences due to the size of the first stage F-statistics of this measure.

We examine the robustness of the results using balanced panel households and the children who are 5 to 17 years old at the baseline survey year to ensure that our results do not come from a sample composition. Table A9 and A10 shows that this is not the case, and our results are robust to different ways to restrict the sample.

7 Conclusion

Drought-prone areas often lack access to formal insurance markets where households can purchase insurance products to mitigate the risk of adverse shocks. Combined with strong demand for labor supply within the household and a limited supply of quality education, children from drought-prone pastoral communities are likely to be exposed to child labor and low school enrollment. Index-based microinsurance has been receiving increased research attention to protect the welfare of the household from such adverse shocks. However, the effects on the individuals within the insured households are not well understood. This paper aims to fill this gap in the literature using the exogenous variation in the price of Index-Based Livestock Insurance, created by coupons randomly distributed to the households in the Marsabit district of Kenya and the Borena zone of Ethiopia.

Employing the instrumental variables approach with individual fixed effects, we find that insurance increases households' investment in children's human capital. Specifically, children decrease participation in part-time work and schooling and increase full-time schooling on average. Moreover, the insurance prevents children's participation in livestock-related work as children's primary activities increase upon drought shock, while children households without insurance coverage increase their participation. The effects are robust to various specifications and sample restriction criteria. We find that the effects are driven by the changes in herding strategies and in herd sizes.

The insurance effects differ depending on the demographic characteristic of children. Although full-time schooling increases among all children, children of primary school age and younger siblings are more likely to reduce participation in heavier types of work while teenagers and the oldest siblings shift from part-time work to full-time schooling. While we do not find statistically significant differences of the effects across gender, we do find suggestive evidence that the girls are more likely to be protected by the insurance from part-time work and schooling upon drought shock, while boys are more likely to work less during non-shock periods due to the insurance.

The paper does not disentangle the effect of insurance on child labor usage as an ex-post loss mitigation strategy due to the recall period in measuring the child work and schooling. Moreover, although it shows the increase in full-time schooling, the paper does not examine whether the increase in investment in children's human capital actually leads to human capital accumulation. It requires further examination in a couple of dimensions. First, it needs an evaluation of children's human capital. It could be measured in academic achievement or more general human capital, such as cognitive ability. Secondly, it requires a better measurement of child labor, such as work in hazardous labor conditions. All of which are important aspects and should be the topic of further research.

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Figure 1: Map of project areas

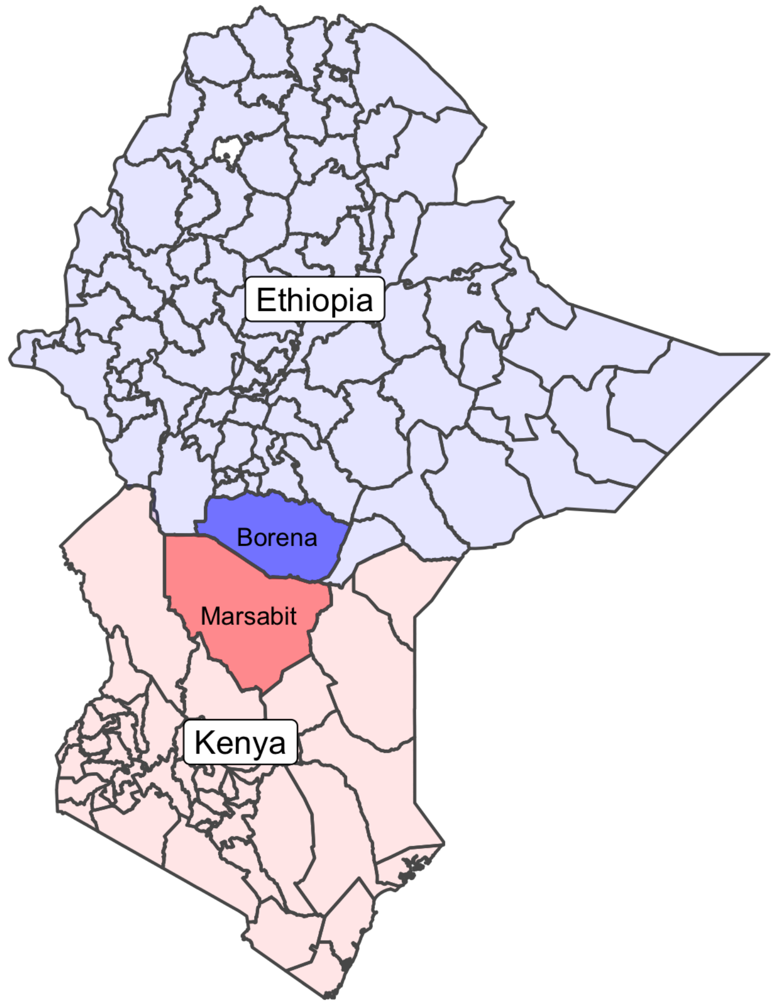
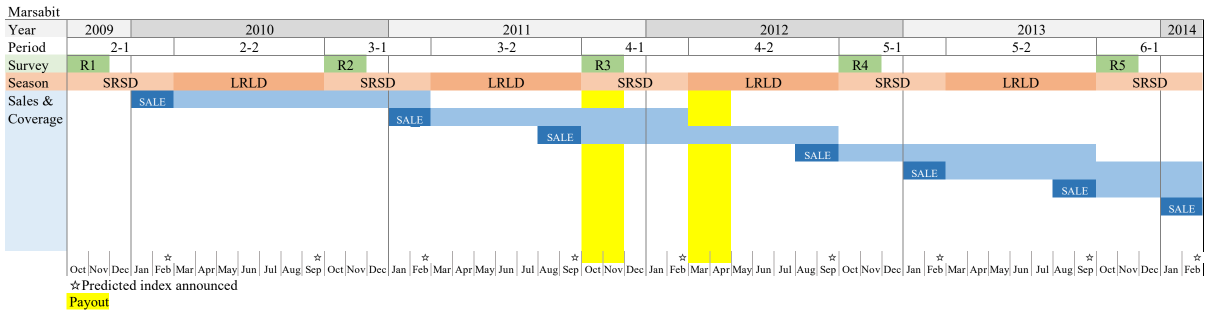


Figure 2: Timeline of the projects

(a) Marsabit District, Kenya



(b) Borena Zone, Ethiopia

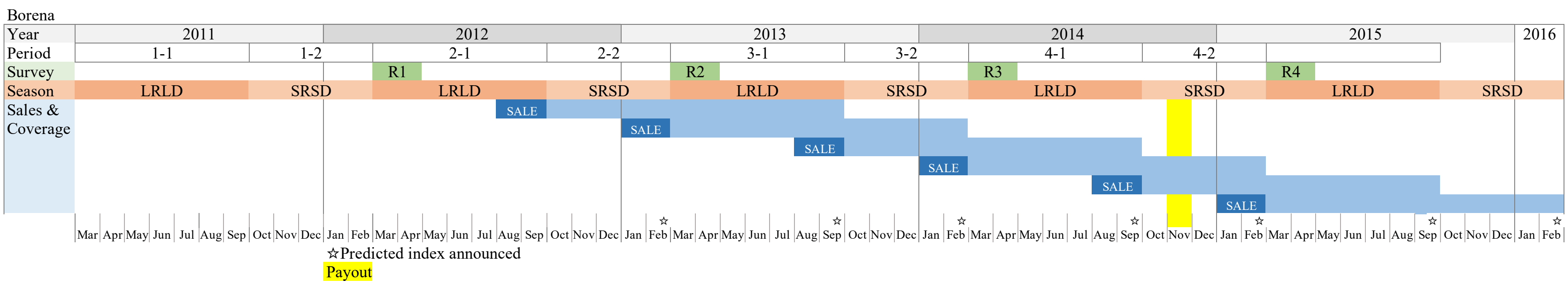
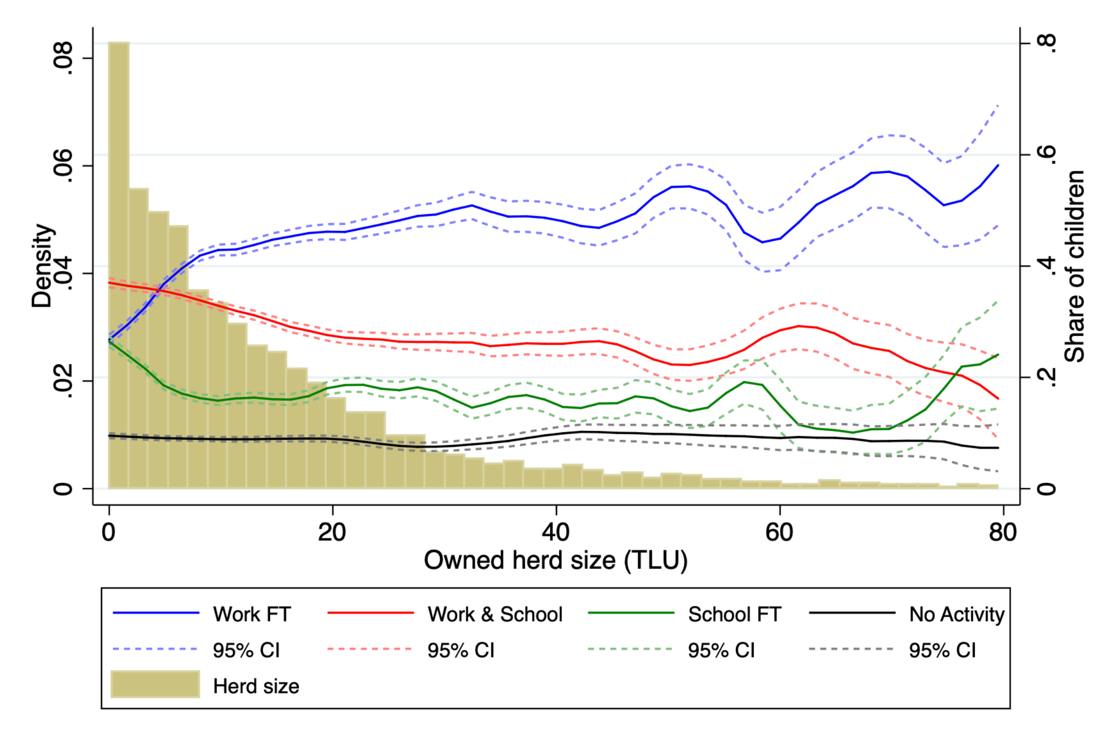


Figure 3: Children's activity by herd size

(a) Participation



(b) Hours, equals to zero if not participating

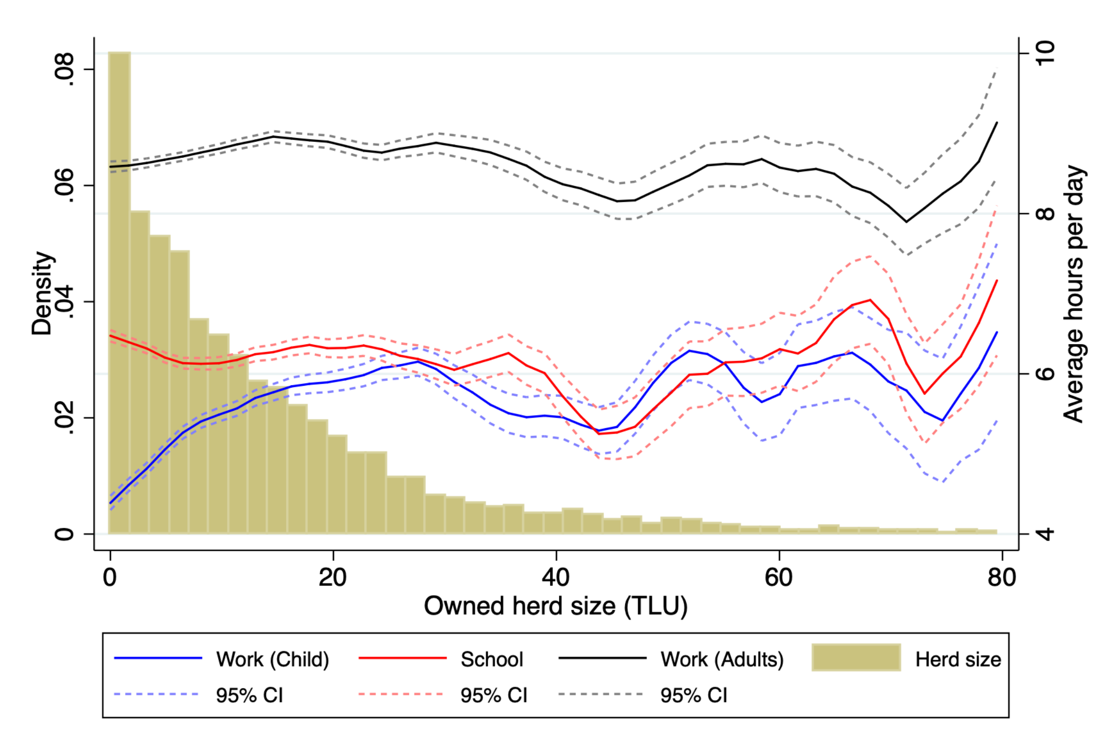
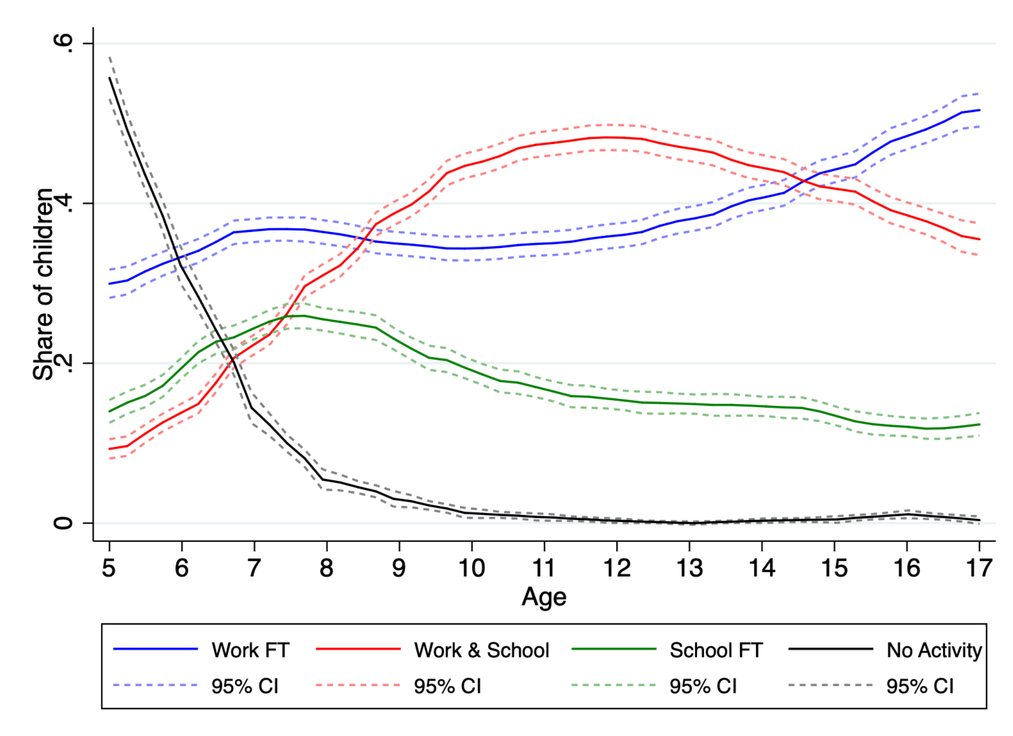


Figure 4: Children's activity by age and gender

(a) Girls



(b) Boys

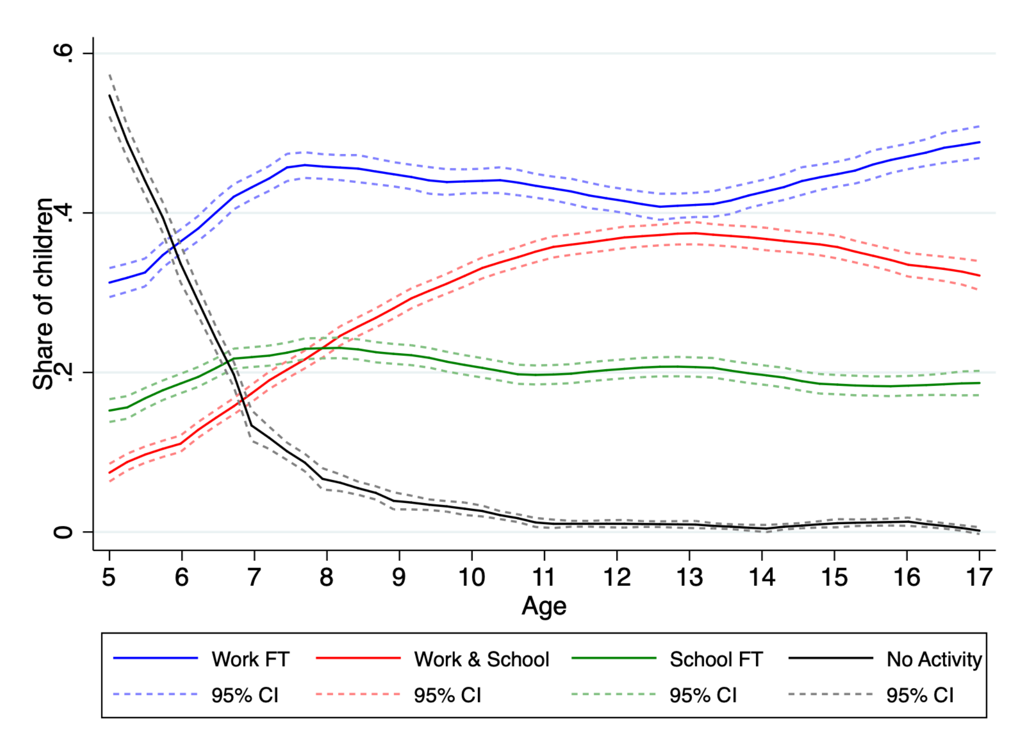
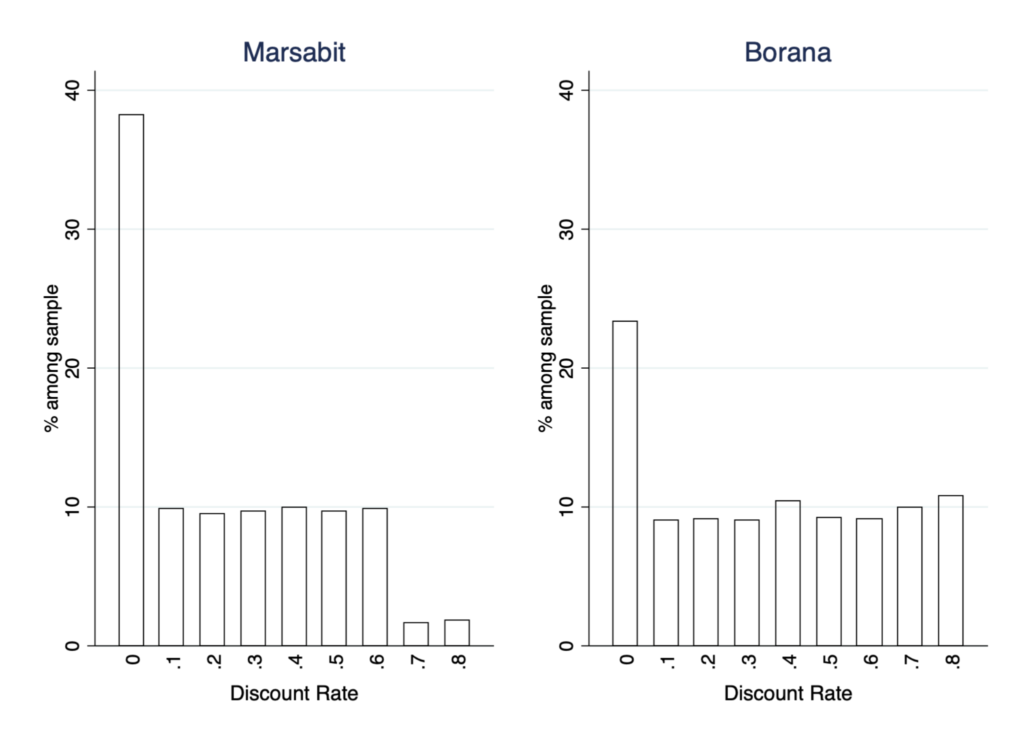


Figure 5: Discount Rate and Insured Livestock

(a) Discount Rates



(b) Livestock (TLU) insured, conditional on insurance purchase

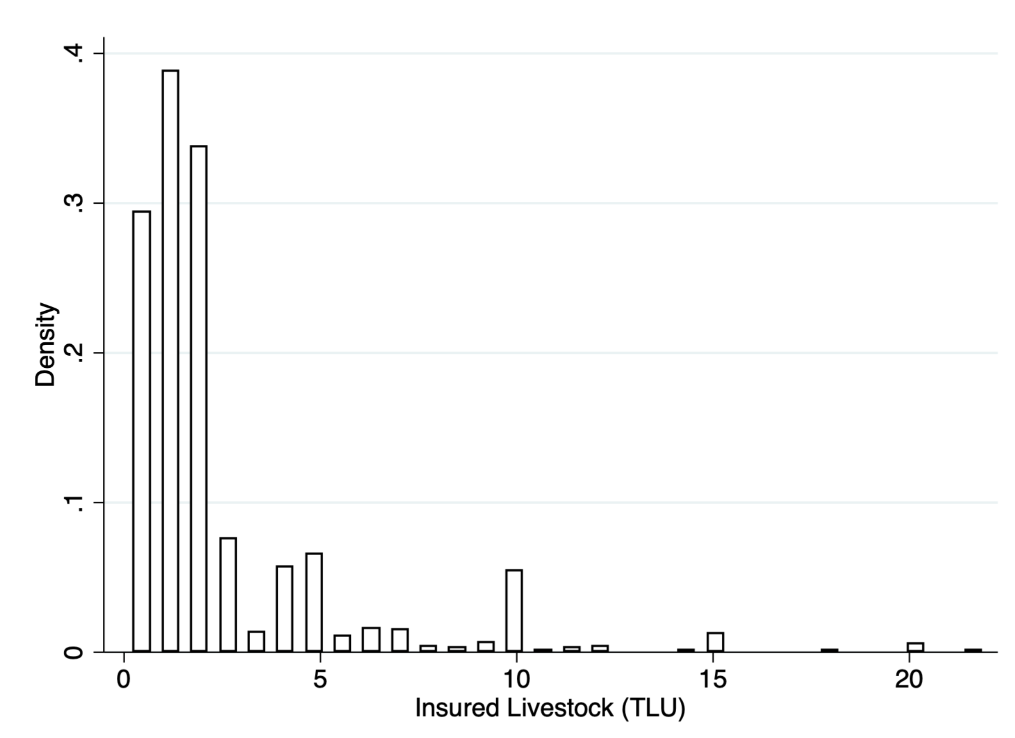


Table 1: Balance between recipients and non-recipients of coupon

	Coupon		No Coupon		Coupon vs. No Coupon		
	Mean	SD	Mean	SD	Difference	SE	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Household Characteristics							
Head age	49.3	[17.6]	47.9	[16.7]	0.536	(0.599)	9594
Head Male	0.659	[0.474]	0.638	[0.480]	-0.0212	(0.0155)	9598
Adult Equivalent	4.78	[2.07]	4.43	[2.08]	0.0227	(0.0587)	9624
Herd size	14.1	[23.0]	13.6	[21.7]	-0.109	(0.667)	9640
Consumption expenditure	35360.2	[343747.7]	34268.0	[225161.3]	8341.1	(8900.4)	9638
Livestock expenditure	1672.2	[5423.4]	2303.5	[8047.5]	-248.1	(192.0)	9623
Joint test, p-val:					0.340		
Panel B: Individual Characteristics							
Age	10.8	[3.64]	10.8	[3.64]	0.192**	(0.0950)	13910
Female	0.458	[0.498]	0.460	[0.498]	-0.00634	(0.0123)	13910
Work FT	0.425	[0.494]	0.412	[0.492]	0.00629	(0.0144)	13888
Work and school	0.284	[0.451]	0.285	[0.452]	-0.00561	(0.0137)	13910
School FT	0.191	[0.393]	0.208	[0.406]	-0.000200	(0.0160)	13910
No Activity	0.100	[0.300]	0.0942	[0.292]	-0.000684	(0.00673)	13888
Hr: Work	6.01	[4.71]	4.99	[4.93]	-0.0164	(0.116)	5616
Hr: School	5.77	[4.14]	5.14	[4.53]	-0.0702	(0.0844)	6844
Hr: Leisure	18.7	[4.55]	19.4	[4.73]	0.0600	(0.0823)	13910
Joint test, p-val:					0.569		

Notes: Column 1 to 4 reports mean and stadard deviation of variables for subjects received and not received discount coupon. Columns 5 and 6 report mean differences between the two groups. Standard deviations are in brackets, and standard errors are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table 2: 1st Stage Correlation

	Insurance Uptake (Cum.)	Shock $\times$ Insurance Uptake (Cum.)	Insurance Uptake (Cum.)
	(1)	(2)	(3)
Discount rate (Current + Cum.)	0.326***	0.043***	0.359***
	(0.031)	(0.011)	(0.030)
Shock $\times$ Discount rate (Cum.)	0.001	0.004***	
	(0.001)	(0.001)	
N	10811	10811	10811

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Discount rate (Cum.) is the sum of discount rates provided by the coupon over the latest three seasons. Relevant periods for insurance uptake are the same as those of the discount rate. All specifications include individual-, insurance area-, survey year- fixed effects, adult equivalent, age and age-squared, female dummy, age and sex of the household head, and tge number of children in the household.

Table 3: Impact on Child Activities

	Child Labor	Work FT	Work and School	School FT	No activity
	(1)	(2)	(3)	(4)	(5)
Panel A: Average Effects					
Insurance Uptake (Cum.)	-0.085**	-0.024	-0.101***	0.122***	0.035
	(0.043)	(0.033)	(0.038)	(0.035)	(0.026)
N	11744	11744	11744	11744	11744
F_{eff}	52.715	52.715	52.715	52.715	52.715
5% Critical Value	37.418	37.418	37.418	37.418	37.418
10% Critical Value	23.109	23.109	23.109	23.109	23.109
AR test p-val.	0.044	0.464	0.007	0.000	0.167
Mean of Dep. Var.	0.431	0.392	0.251	0.164	0.111
Panel B: Disaggregated Effects					
Shock	0.096**	0.009	0.046	-0.038	-0.001
	(0.040)	(0.022)	(0.035)	(0.035)	(0.018)
Insurance Uptake (Cum.)	-0.044	-0.019	-0.098**	0.116***	0.043
	(0.055)	(0.045)	(0.047)	(0.043)	(0.034)
Shock $\times$ Insurance Uptake (Cum.)	-0.180*	-0.021	-0.046	0.046	-0.017
	(0.100)	(0.065)	(0.088)	(0.088)	(0.051)
Shock+Uptake $\times$ Shock (coef.)	-0.084	-0.012	0.001	0.008	-0.018
Shock+Uptake $\times$ Shock (p-val.)	0.238	0.814	0.993	0.896	0.650
N	10811	10811	10811	10811	10811
K-P F-stat	25.457	25.457	25.457	25.457	25.457
AR test p-val.	0.009	0.672	0.017	0.001	0.383
Mean of Dep. Var.	0.535	0.406	0.314	0.180	0.079

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Insurance uptake (Cum.) is the sum of discount rates provided by the coupon over the three seasons prior to the interview. All specifications include individual-, insurance area-, survey year-fixed effects, adult equivalent, age, age-squared, female dummy, age and sex of the household head, number of children in the household.

Table 4: Impact on Various Types of Child Activities

	Primary Activity				Secondary Activity			
	Any work	Livestock related tasks	HH tasks	School	Any work	Livestock related tasks	HH Tasks	School
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Average Effects								
Insurance Uptake (Cum.)	0.012	0.006	0.013	-0.008	-0.205***	-0.063*	-0.099**	0.031**
	(0.034)	(0.032)	(0.029)	(0.029)	(0.054)	(0.038)	(0.045)	(0.013)
N	11743	11743	11743	11743	11744	11744	11744	11744
F_{eff}	52.645	52.645	52.645	52.645	52.715	52.715	52.715	52.715
5% Critical Value	37.418	37.418	37.418	37.418	37.418	37.418	37.418	37.418
10% Critical Value	23.109	23.109	23.109	23.109	23.109	23.109	23.109	23.109
AR test p-val.	0.724	0.852	0.660	0.789	0.000	0.094	0.021	0.014
Mean of Dep. Var.	0.394	0.267	0.108	0.410	0.384	0.124	0.233	0.005
Panel B: Disaggregated Effects								
Shock	0.021	0.056**	-0.030	-0.004	0.060	-0.035	0.074*	0.025***
	(0.021)	(0.022)	(0.021)	(0.021)	(0.047)	(0.029)	(0.044)	(0.009)
Insurance Uptake (Cum.)	0.027	0.025	0.008	-0.017	-0.211***	-0.065	-0.108**	0.039**
	(0.045)	(0.043)	(0.037)	(0.037)	(0.068)	(0.050)	(0.053)	(0.018)
Shock × Insurance Uptake (Cum.)	-0.053	-0.092	0.037	0.027	-0.034	0.031	-0.036	-0.040
	(0.063)	(0.066)	(0.056)	(0.060)	(0.125)	(0.071)	(0.111)	(0.030)
Shock+Uptake × Shock (coef.)	-0.032	-0.036	0.007	0.023	0.026	-0.004	0.038	-0.014
Shock+Uptake × Shock (p-val.)	0.516	0.481	0.876	0.613	0.778	0.945	0.624	0.558
N	10810	10810	10810	10810	10811	10811	10811	10811
K-P F-stat	25.505	25.505	25.505	25.505	25.457	25.457	25.457	25.457
AR test p-val.	0.692	0.325	0.607	0.873	0.000	0.394	0.031	0.069
Mean of Dep. Var.	0.412	0.310	0.089	0.487	0.446	0.152	0.270	0.009

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Insurance uptake (Cum.) is the sum of discount rates provided by the coupon over the three seasons prior to the interview. All specifications include individual-, insurance area-, survey year- fixed effects, adult equivalent, age, age-squared, female dummy, age and sex of the household head, number of children in the household.

Table 5: Impact on Herding Stratgeies

	Mobile	Share of livestock kept away	N of type of livestock	N of income sources
	(1)	(2)	(3)	(4)
Shock	-0.030	0.032	-0.003	-0.083
	(0.043)	(0.033)	(0.042)	(0.083)
Insurance Uptake (Cum.)	0.216***	0.225***	0.059	-0.138
	(0.072)	(0.057)	(0.061)	(0.123)
Shock $\times$ Insurance Uptake (Cum.)	-0.200*	-0.204**	-0.018	0.093
	(0.116)	(1.925)	(0.101)	(0.215)
Shock+Uptake $\times$ Shock (coef.)	-0.230	-0.172	-0.021	0.011
Shock+Uptake $\times$ Shock (p-val.)	0.009	0.012	0.771	0.945
N	4875	4633	4875	4875
K-P F-stat	32.362	30.585	32.362	32.362
AR test p-val.	0.007	0.000	0.596	0.521
Mean of Dep. Var.	0.600	0.633	1.975	1.578

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table 6: Impact on Household outcome in Response to Shock

	Food expenditure	Non-food expenditure	Livestock expenditure (Total)	Livestock food	Livestock Veterinary
	(1)	(2)	(3)	(4)	(5)
Shock	-1.684*	-1.400	0.180	0.019	0.062
	(0.869)	(1.348)	(0.157)	(0.111)	(0.042)
Insurance Uptake (Cum.)	-1.183	0.453	0.424**	0.279**	-0.059
	(1.210)	(1.181)	(0.215)	(0.127)	(0.048)
Shock × Insurance Uptake (Cum.)	0.887	-0.020	-0.551	-0.269	0.018
	(2.237)	(2.500)	(0.423)	(0.329)	(0.117)
Shock+Uptake × Shock (coef.)	-0.797	-1.419	-0.371	-0.250	0.080
Shock+Uptake × Shock (p-val.)	0.618	0.359	0.241	0.286	0.328
N	4872	4865	4863	4863	4863
K-P F-stat	32.444	32.562	32.483	32.483	32.483
AR test p-val.	0.603	0.921	0.109	0.076	0.468
Mean of Dep. Var.	15.844	8.182	0.624	0.334	0.185

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table 7: Impact on Herd Size

	Herd size (own)	Herd size (herding)	Adult animals	Lactating animals	Milk Production	Milk Sale
	(1)	(2)	(3)	(4)	(5)	(6)
Shock	2.597***	4.547***	2.279***	0.862*	31.412	349.504*
	(0.953)	(1.174)	(0.842)	(0.508)	(375.775)	(194.346)
Insurance Uptake (Cum.)	2.890	1.414	-0.161	-1.056*	71.190	285.154
	(1.768)	(2.130)	(1.578)	(0.632)	(499.624)	(256.990)
Shock × Insurance Uptake (Cum.)	-4.356*	-5.685**	-2.793	-0.264	-222.979	-819.143*
	(2.394)	(2.865)	(1.917)	(1.178)	(1022.953)	(492.014)
Shock+Uptake × Shock (coef.)	-1.758	-1.138	-0.515	0.599	-191.567	-469.639
Shock+Uptake × Shock (p-val.)	0.311	0.569	0.702	0.453	0.797	0.167
N	4875	4875	4875	4875	4875	4875
K-P F-stat	32.362	32.362	32.362	32.362	32.362	32.362
AR test p-val.	0.158	0.112	0.231	0.177	0.976	0.205
Mean of Dep. Var.	13.507	14.772	9.783	3.972	3515.991	395.668

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table 8: Impact on Herd Size and Children's work by Initial Herd Size

	Smallest Quintile	Second Quintile	Third Quintile	Fourth Quitile	Largest Quintile
	(1)	(2)	(3)	(4)	(5)
Panel A: Effects on Herd size					
Shock	-2.307*	0.242	2.745	0.151	8.592**
	(1.220)	(0.646)	(1.786)	(2.097)	(4.232)
Insurance Uptake (Cum.)	-0.243	5.345**	1.304	2.641	4.253
	(1.759)	(2.186)	(3.486)	(2.442)	(4.482)
Shock $\times$ Insurance Uptake (Cum.)	5.754	-3.981	-6.732	1.932	-10.987
	(4.941)	(2.512)	(4.113)	(3.957)	(7.122)
Shock+Uptake $\times$ Shock (coef.)	3.447	-3.739	-3.988	2.083	-2.394
Shock+Uptake $\times$ Shock (p-val.)	0.372	0.077	0.179	0.394	0.606
N	910	948	936	926	939
K-P F-stat	1.417	10.256	6.342	10.831	10.336
AR test p-val.	0.138	0.020	0.170	0.202	0.326
Mean of Dep. Var.	3.599	7.786	14.394	29.840	.
Panel B: Effects on Children's Livestock-related Tasks					
Shock	0.083	0.017	0.078	0.080	0.050
	(0.073)	(0.045)	(0.068)	(0.052)	(0.057)
Insurance Uptake (Cum.)	0.077	0.176	-0.009	0.014	-0.044
	(0.137)	(0.150)	(0.180)	(0.069)	(0.057)
Shock $\times$ Insurance Uptake (Cum.)	-0.211	-0.285	-0.010	-0.050	-0.057
	(0.326)	(0.174)	(0.196)	(0.110)	(0.108)
Shock+Uptake $\times$ Shock (coef.)	-0.128	-0.268	0.068	0.030	-0.008
Shock+Uptake $\times$ Shock (p-val.)	0.628	0.064	0.650	0.718	0.918
N	1757	1998	2114	2108	2346
K-P F-stat	1.309	6.552	4.569	9.810	8.036
AR test p-val.	0.779	0.186	0.991	0.894	0.407
Mean of Dep. Var.	0.202	0.272	0.367	0.368	.

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table 9: Impact on Child Activities, by Age

	Child Labor	Work FT	Work and School	School FT	Work as Primary	Work as Secondary
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Heterogeneity of Average Effects						
Age 5-12 × Insurance Uptake (Cum.)	-0.154***	-0.030	-0.075	0.105**	-0.003	-0.199***
	(0.059)	(0.047)	(0.046)	(0.041)	(0.048)	(0.063)
Age 13-17 × Insurance Uptake (Cum.)	-0.036	0.002	-0.207***	0.187***	0.059	-0.279***
	(0.072)	(0.047)	(0.076)	(0.068)	(0.047)	(0.102)
Difference	-0.118	-0.032	0.132	-0.083	-0.062	0.080
	(0.091)	(0.067)	(0.084)	(0.074)	(0.067)	(0.111)
N	11744	11744	11744	11744	11743	11744
Panel B: Disaggreagted Effects, Children of Age 5-12						
Shock	0.110**	0.003	0.016	0.011	0.012	0.030
	(0.055)	(0.032)	(0.042)	(0.043)	(0.033)	(0.055)
Insurance Uptake (Cum.)	-0.110	-0.023	-0.058	0.089*	-0.001	-0.172**
	(0.074)	(0.064)	(0.055)	(0.051)	(0.065)	(0.078)
Shock × Insurance Uptake (Cum.)	-0.208	-0.021	-0.055	0.028	-0.015	-0.094
	(0.139)	(0.091)	(0.102)	(0.108)	(0.094)	(0.143)
Shock+Uptake × Shock (coef.)	-0.098	-0.018	-0.038	0.039	-0.003	-0.064
Shock+Uptake × Shock (p-val.)	0.326	0.803	0.604	0.617	0.964	0.539
N	6573	6573	6573	6573	6573	6573
K-P F-stat	0.535	0.406	0.314	0.180	0.412	0.446
Panel C: Disaggreagted Effects, Children of Age 13-17						
Shock	0.127**	0.043*	0.080	-0.122**	0.058**	0.093
	(0.055)	(0.024)	(0.061)	(0.061)	(0.025)	(0.075)
Insurance Uptake (Cum.)	-0.009	0.016	-0.239***	0.195**	0.100*	-0.329***
	(0.086)	(0.061)	(0.091)	(0.077)	(0.060)	(0.124)
Shock × Insurance Uptake (Cum.)	-0.175	-0.074	0.027	0.074	-0.159**	0.068
	(0.133)	(0.070)	(0.152)	(0.148)	(0.071)	(0.196)
Shock+Uptake × Shock (coef.)	-0.048	-0.032	0.106	-0.049	-0.102	0.161
Shock+Uptake × Shock (p-val.)	0.613	0.567	0.327	0.639	0.076	0.263
N	3703	3703	3703	3703	3703	3703
K-P F-stat	0.535	0.406	0.314	0.180	0.412	0.446

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Insurance uptake (Cum.) is the sum of discount rates provided by the coupon over the three seasons prior to the interview. Shock is an indicator if an insurance area is affected by the drought in that year. All specifications include individual-, insurance area-, survey year- fixed effects, adult equivalent, age, age-squared, female dummy, age and sex of the household head, number of children in the household.

Table 10: Impact on Child Activities, by Birth Order

	Child Labor	Work FT	Work and School	School FT	Work as Primary	Work as Secondary
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Heterogeneity of Average Effects						
1st born × Insurance Uptake (Cum.)	-0.050	0.073	-0.244***	0.160***	0.132**	-0.389***
	(0.081)	(0.063)	(0.069)	(0.060)	(0.064)	(0.102)
Others × Insurance Uptake (Cum.)	-0.112**	-0.084**	-0.020	0.101***	-0.057	-0.125**
	(0.051)	(0.040)	(0.039)	(0.038)	(0.040)	(0.056)
Difference	0.062	0.157**	-0.224***	0.059	0.189**	-0.264**
	(0.095)	(0.074)	(0.076)	(0.066)	(0.075)	(0.109)
N	11744	11744	11744	11744	11743	11744
Panel B: Disaggreagted Effects, Oldest siblings						
Shock	0.138**	0.036	0.011	-0.018	0.061**	-0.011
	(0.057)	(0.027)	(0.050)	(0.050)	(0.027)	(0.062)
Insurance Uptake (Cum.)	0.072	0.121	-0.251***	0.142*	0.213**	-0.475***
	(0.109)	(0.091)	(0.089)	(0.077)	(0.092)	(0.138)
Shock × Insurance Uptake (Cum.)	-0.363**	-0.131	0.008	0.052	-0.219**	0.194
	(0.157)	(0.104)	(0.138)	(0.139)	(0.096)	(0.188)
Shock+Uptake × Shock (coef.)	-0.225	-0.095	0.018	0.033	-0.158	0.183
Shock+Uptake × Shock (p-val.)	0.063	0.286	0.863	0.752	0.057	0.214
N	3519	3519	3519	3519	3519	3519
K-P F-stat	0.535	0.406	0.314	0.180	0.412	0.446
Panel C: Disaggreagted Effects, Younger siblings						
Shock	0.051	-0.008	0.035	-0.018	-0.009	0.056
	(0.050)	(0.036)	(0.043)	(0.041)	(0.036)	(0.054)
Insurance Uptake (Cum.)	-0.122*	-0.094*	-0.035	0.113**	-0.078	-0.137*
	(0.066)	(0.056)	(0.049)	(0.047)	(0.056)	(0.072)
Shock × Insurance Uptake (Cum.)	-0.015	0.030	0.010	-0.016	0.062	-0.014
	(0.120)	(0.090)	(0.097)	(0.093)	(0.094)	(0.130)
Shock+Uptake × Shock (coef.)	0.036	0.022	0.045	-0.034	0.053	0.043
Shock+Uptake × Shock (p-val.)	0.668	0.734	0.502	0.596	0.443	0.641
N	6679	6679	6679	6679	6678	6679
K-P F-stat	0.535	0.406	0.314	0.180	0.412	0.446

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Insurance uptake (Cum.) is the sum of discount rates provided by the coupon over the three seasons prior to the interview. All specifications include individual-, insurance area-, survey year- fixed effects, adult equivalent, age, age-squared, female dummy, age and sex of the household head, number of children in the household.

Table 11: Impact on Child Activities, by Gender

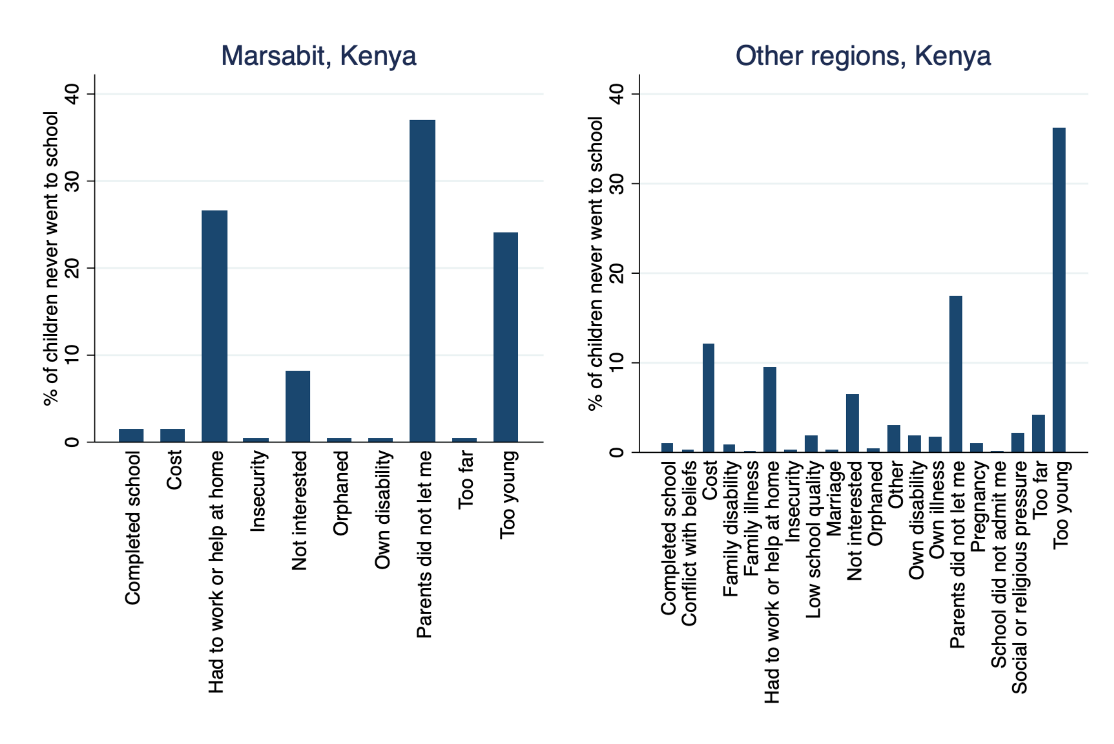
	Child Labor	Work FT	Work and School	School FT	Work as Primary	Work as Secondary
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Heterogeneity of Average Effects						
Female × Insurance Uptake (Cum.)	-0.126**	-0.040	-0.107**	0.103**	0.019	-0.187***
	(0.059)	(0.047)	(0.051)	(0.041)	(0.048)	(0.068)
Male × Insurance Uptake (Cum.)	-0.041	-0.009	-0.090*	0.142***	0.005	-0.218***
	(0.060)	(0.046)	(0.050)	(0.052)	(0.045)	(0.073)
Difference	-0.085	-0.031	-0.017	-0.039	0.014	0.031
	(0.082)	(0.065)	(0.067)	(0.061)	(0.065)	(0.092)
N	11744	11744	11744	11744	11743	11744
Panel B: Disaggreagted Effects, Girls						
Shock	0.195***	-0.012	0.128**	-0.123**	0.004	0.116
	(0.069)	(0.033)	(0.056)	(0.055)	(0.033)	(0.079)
Insurance Uptake (Cum.)	-0.036	-0.015	-0.056	0.039	0.048	-0.097
	(0.076)	(0.065)	(0.063)	(0.055)	(0.067)	(0.087)
Shock × Insurance Uptake (Cum.)	-0.375**	-0.051	-0.228	0.255*	-0.074	-0.312
	(0.177)	(0.093)	(0.142)	(0.146)	(0.094)	(0.211)
Shock+Uptake × Shock (coef.)	-0.181	-0.063	-0.100	0.133	-0.070	-0.196
Shock+Uptake × Shock (p-val.)	0.139	0.378	0.311	0.197	0.336	0.180
N	5179	5179	5179	5179	5179	5179
K-P F-stat	0.535	0.406	0.314	0.180	0.412	0.446
Panel C: Disaggreagted Effects, Boys						
Shock	0.023	0.032	-0.021	0.030	0.038	0.020
	(0.046)	(0.029)	(0.041)	(0.043)	(0.028)	(0.055)
Insurance Uptake (Cum.)	-0.045	-0.022	-0.131**	0.190***	0.005	-0.309***
	(0.076)	(0.059)	(0.063)	(0.064)	(0.058)	(0.097)
Shock × Insurance Uptake (Cum.)	-0.007	0.010	0.121	-0.147	-0.030	0.218
	(0.120)	(0.087)	(0.106)	(0.104)	(0.083)	(0.151)
Shock+Uptake × Shock (coef.)	0.016	0.042	0.100	-0.116	0.008	0.239
Shock+Uptake × Shock (p-val.)	0.858	0.549	0.201	0.124	0.901	0.035
N	5590	5590	5590	5590	5589	5590
K-P F-stat	0.535	0.406	0.314	0.180	0.412	0.446

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Insurance uptake (Cum.) is the sum of discount rates provided by the coupon over the three seasons prior to the interview. All specifications include individual-, insurance area-, survey year- fixed effects, adult equivalent, age, age-squared, female dummy, age and sex of the household head, number of children in the household.

A Appendix: Additional Figures and Tables

Figure A1: Reason why children never attended school

(a) Marsabit District, Kenya



(b) Borena Zone, Ethiopia

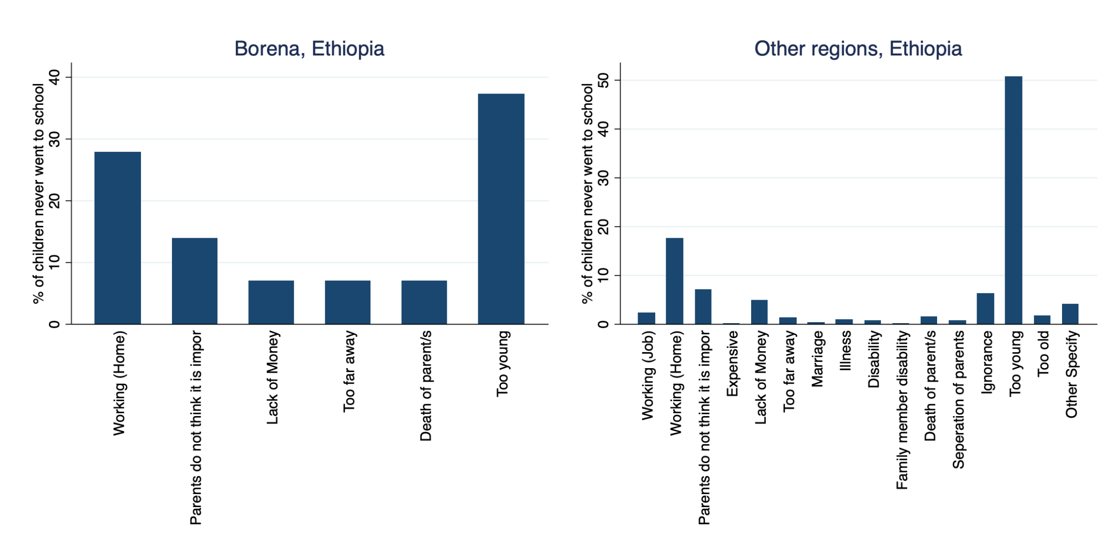
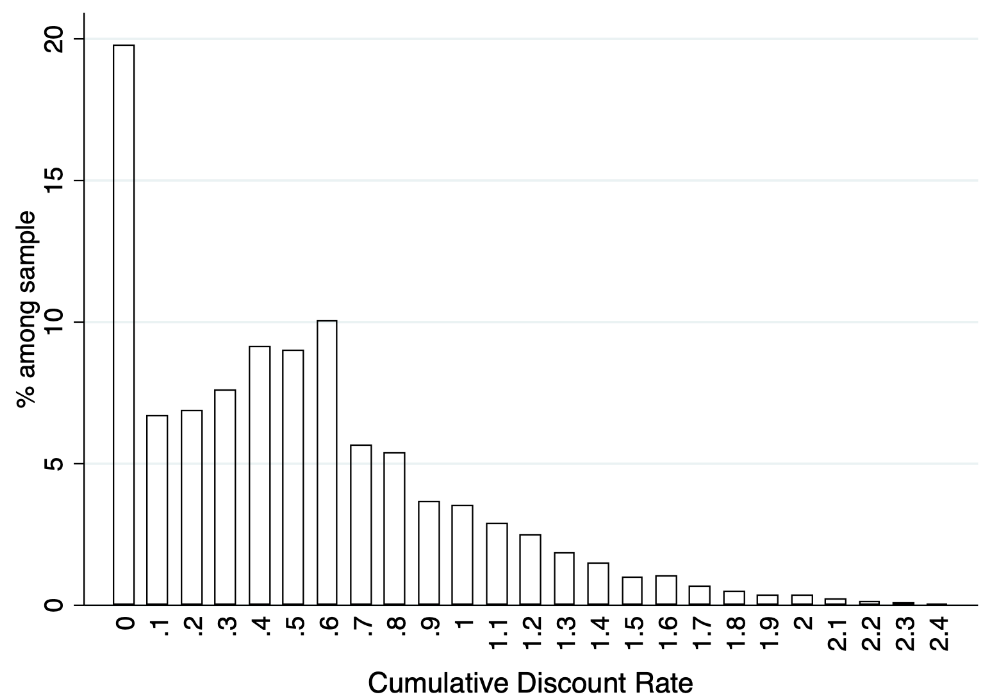


Figure A2: Cumulative discount rate and Insurance take-up

(a) Cumulative Discount Rates, the three recent sales seaons



(b) Total number of Insurance Take-up, the three recent sales seasons

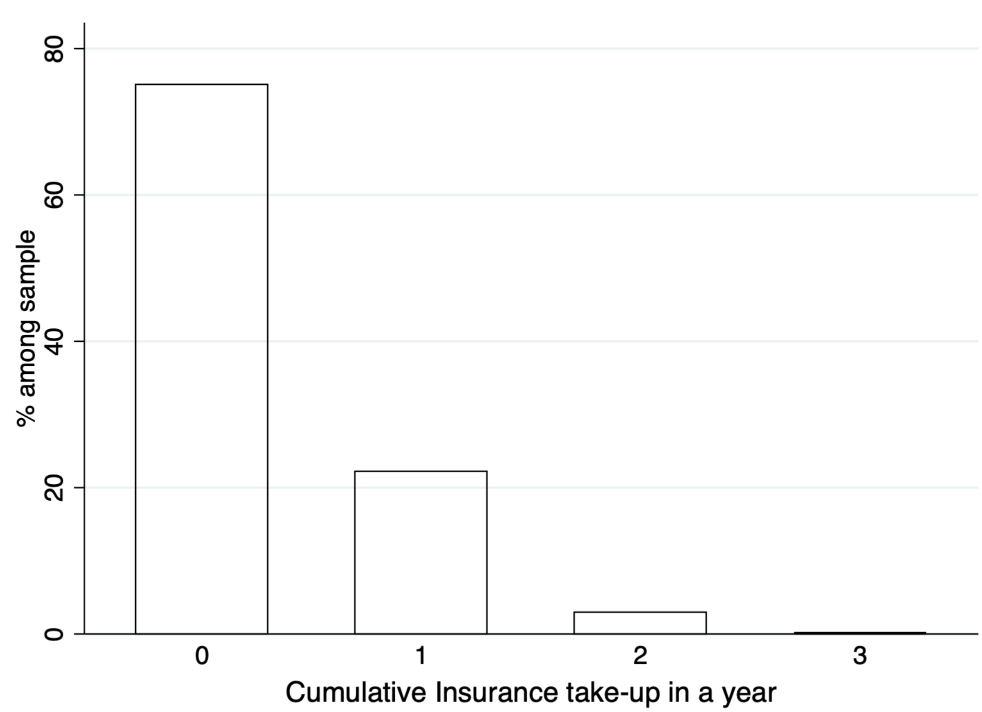


Table A1: First-stage predictive power of Table 3, Panel B

Panel A					
Shock	0.042*	0.003	0.032	-0.024	-0.006
	(0.023)	(0.015)	(0.021)	(0.021)	(0.012)
Insurance Uptake (Cum.)	-0.110**	-0.027	-0.114***	0.133***	0.036
	(0.047)	(0.035)	(0.041)	(0.039)	(0.027)
N	11744	11744	11744	11744	11744
F_{eff}	24.714	24.714	24.714	24.714	24.714
5% Critical Value	6.278	4.450	4.874	5.179	7.221
10% Critical Value	4.819	3.771	4.010	4.185	5.366
AR test p-val.	0.009	0.672	0.017	0.001	0.383
Mean of Dep. Var.	0.431	0.392	0.251	0.164	0.111
Panel B					
Shock	0.102***	0.012	0.061*	-0.056	-0.008
	(0.039)	(0.021)	(0.034)	(0.035)	(0.017)
Shock $\times$ Insurance Uptake (Cum.)	-0.223***	-0.040	-0.141*	0.160**	0.025
	(0.085)	(0.050)	(0.076)	(0.076)	(0.039)
N	11744	11744	11744	11744	11744
F_{eff}	14.274	14.274	14.274	14.274	14.274
5% Critical Value	31.459	31.456	31.456	31.456	31.462
10% Critical Value	19.617	19.615	19.615	19.615	19.619
AR test p-val.	0.009	0.672	0.017	0.001	0.383
Mean of Dep. Var.	0.431	0.392	0.251	0.164	0.111

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Insurance uptake (Cum.) is the sum of discount rates provided by the coupon over the three seasons prior to the interview. Shock is an indicator if an insurance area is affected by the drought in that year. All specifications include individual-, insurance area-, survey year- fixed effects, adult equivalent, age, age-squared, female dummy, age and sex of the household head, number of children in the household.

Table A2: Impact on Children's Working Hours Conditional on Working

	Child Labor	Work FT	Work and School	School FT	No activity
	(1)	(2)	(3)	(4)	(5)
Panel A: Average Effects					
Insurance Uptake (Cum.)	-0.230	-0.762*	0.413	-2.125	0.505
	(0.349)	(0.430)	(0.296)	(1.301)	(0.309)
N	6376	4767	3738	2062	11744
F_{eff}	32.731	30.106	18.371	2.388	52.715
5% Critical Value	37.418	37.418	37.418	37.418	37.418
10% Critical Value	23.109	23.109	23.109	23.109	23.109
AR test p-val.	0.506	0.063	0.161	0.046	0.097
Mean of Dep. Var.	5.870	7.319	3.001	6.941	17.166
Panel B: Disaggregated Effects					
Shock	0.114	0.182	0.376*	-3.298	-0.428*
	(0.304)	(0.522)	(0.206)	(8.284)	(0.253)
Insurance Uptake (Cum.)	-0.776	-1.759***	0.820**	-22.144	0.722*
	(0.474)	(0.609)	(0.370)	(58.999)	(0.393)
Shock × Insurance Uptake (Cum.)	1.260	2.441**	-1.423**	20.017	-0.191
	(0.838)	(1.205)	(0.562)	(52.866)	(0.667)
Shock+Uptake × Shock (coef.)	1.374	2.623	-1.047	16.719	-0.620
Shock+Uptake × Shock (p-val.)	0.030	0.001	0.013	0.708	0.205
N	5110	3864	2902	1133	10811
K-P F-stat	12.342	7.227	11.672	0.068	25.457
AR test p-val.	0.199	0.004	0.017	0.062	0.113
Mean of Dep. Var.	6.824	8.149	2.993	7.115	16.274

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Insurance uptake (Cum.) is the sum of discount rates provided by the coupon over the three seasons prior to the interview. All specifications include individual-, insurance area-, survey year-fixed effects, adult equivalent, age, age-squared, female dummy, age and sex of the household head, number of children in the household.

Table A3: Impact on Various Types of Child Activities

	Primary Activity				Secondary Activity			
	Any work	Livestock related tasks	HH tasks	School	Any work	Livestock related tasks	HH Tasks	School
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Average Effects								
Insurance Uptake (Cum.)	-0.496	-0.509	-0.250	-0.291	0.126	0.419	-0.206	4.976
	(0.363)	(0.392)	(1.403)	(0.305)	(0.190)	(0.293)	(0.343)	(3.027)
N	4849	3724	1005	5691	5280	1833	3147	124
F_{eff}	29.700	21.888	5.909	25.266	27.318	18.463	14.222	6.025
5% Critical Value	37.418	37.418	37.418	37.418	37.418	37.418	37.418	37.418
10% Critical Value	23.109	23.109	23.109	23.109	23.109	23.109	23.109	23.109
AR test p-val.	0.168	0.195	0.859	0.333	0.514	0.137	0.539	0.440
Mean of Dep. Var.	6.514	7.182	5.329	6.750	2.742	2.709	2.773	3.428
Panel B: Disaggregated Effects								
Shock	0.375	0.205	1.321	-0.031	-0.023	0.262	-0.030	12.986**
	(0.398)	(0.410)	(1.081)	(0.145)	(0.167)	(0.358)	(0.260)	(5.447)
Insurance Uptake (Cum.)	-1.142**	-1.248**	-0.432	-0.229	0.053	0.595*	-0.298	4.976
	(0.510)	(0.571)	(1.279)	(0.401)	(0.245)	(0.331)	(0.423)	(3.027)
Shock $\times$ Insurance Uptake (Cum.)	1.413	1.674	-0.996	-0.108	0.170	-0.858	0.188	0.000
	(1.012)	(1.066)	(3.046)	(0.414)	(0.375)	(0.634)	(0.672)	(.)
Shock+Uptake $\times$ Shock (coef.)	1.788	1.879	0.325	-0.139	0.146	-0.596	0.158	12.986
Shock+Uptake $\times$ Shock (p-val.)	0.012	0.016	0.879	0.673	0.603	0.136	0.750	0.017
N	3919	2993	425	5009	3893	865	2057	17
K-P F-stat	6.336	7.460	1.079	22.164	21.614	20.738	7.521	10.948
AR test p-val.	0.056	0.058	0.882	0.539	0.794	0.122	0.770	0.440
Mean of Dep. Var.	7.269	7.772	5.568	7.078	2.827	2.754	2.860	3.188

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Insurance uptake (Cum.) is the sum of discount rates provided by the coupon over the three seasons prior to the interview. All specifications include individual-, insurance area-, survey year- fixed effects, adult equivalent, age, age-squared, female dummy, age and sex of the household head, number of children in the household.

Table A4: Impacts on Household Outcome

	Fully Settled	Share of livestock kept away from home	N of type of livestock	N of income sources
	(1)	(2)	(3)	(4)
Insurance Uptake (Cum.)	-0.128**	-0.157***	0.051	-0.129
	(0.054)	(0.042)	(0.051)	(0.099)
N	4959	4735	4959	4959
F_{eff}	163.414	154.725	163.414	163.414
5% Critical Value	37.418	37.418	37.418	37.418
10% Critical Value	23.109	23.109	23.109	23.109
AR test p-val.	0.015	0.000	0.321	0.193
Mean of Dep. Var.	0.445	0.400	1.777	1.516

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A5: Impacts on Household Outcome

	Food expenditure	Non-food expenditure	Education expenditure	Livestock expenditure (Total)	Livestock food	Livestock Veterinary	Saving
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Insurance Uptake (Cum.)	446.330	-0.020	-0.140	0.269	0.061	-0.031	-11013.290
	(305.208)	(1.029)	(0.312)	(0.187)	(0.040)	(0.050)	(7075.257)
N	4956	4950	4950	4948	4946	4946	4958
F_{eff}	162.193	163.302	163.302	163.541	163.439	163.439	163.518
5% Critical Value	37.418	37.418	37.418	37.418	37.418	37.418	37.418
10% Critical Value	23.109	23.109	23.109	23.109	23.109	23.109	23.109
AR test p-val.	0.142	0.985	0.653	0.148	0.129	0.541	0.120
Mean of Dep. Var.	37.461	6.103	0.774	0.755	0.079	0.148	629.303

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A6: Impacts on Household Herd Size

	Herd size (own)	Herd size (herding)	Adult animals	Lactating animals	Milk Production	Milk Sale
	(1)	(2)	(3)	(4)	(5)	(6)
Insurance Uptake (Cum.)	2.055	0.709	-0.493	-0.872	-5.194	82.169
	(1.364)	(1.710)	(1.330)	(0.558)	(376.932)	(227.277)
N	4959	4959	4959	4959	4959	4959
F_{eff}	163.414	163.414	163.414	163.414	163.414	163.414
5% Critical Value	37.418	37.418	37.418	37.418	37.418	37.418
10% Critical Value	23.109	23.109	23.109	23.109	23.109	23.109
AR test p-val.	0.137	0.679	0.712	0.119	0.989	0.717
Mean of Dep. Var.	13.510	15.269	9.504	3.313	2585.088	356.914

Table A7: Impact on Child Activities with lapsed insurance

	Child Labor	Work FT	Work and School	School FT	No activity
	(1)	(2)	(3)	(4)	(5)
Insurance Uptake (Cum.)	-0.003	0.041	-0.134**	0.100*	0.042
	(0.074)	(0.057)	(0.064)	(0.058)	(0.041)
Insurance Uptake (Lapsed)	0.133	0.105	-0.054	-0.035	0.010
	(0.088)	(0.068)	(0.075)	(0.071)	(0.046)
N	10811	10811	10811	10811	10811
K-P F-stat	26.536	26.536	26.536	26.536	26.536
AR test p-val.	0.026	0.187	0.024	0.001	0.384
Mean of Dep. Var.	0.512	0.387	0.322	0.190	0.084

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Insurance uptake (Cum.) is the sum of discount rates provided by the coupon over the three seasons prior to the interview. All specifications include individual-, insurance area-, survey year- fixed effects, adult equivalent, age, age-squared, female dummy, age and sex of the household head, number of children in the household.

Table A8: Impact on Child Activities using IBLI Coverage in TLU

	Child Labor	Work FT	Work and School	School FT	No activity
	(1)	(2)	(3)	(4)	(5)
Insurance coverage (TLU)	-0.016*	-0.005	-0.019**	0.024***	0.007
	(0.009)	(0.006)	(0.008)	(0.008)	(0.005)
N	11720	11720	11720	11720	11720
F_{eff}	8.939	8.939	8.939	8.939	8.939
5% Critical Value	37.418	37.418	37.418	37.418	37.418
10% Critical Value	23.109	23.109	23.109	23.109	23.109
AR test p-val.	0.041	0.470	0.006	0.000	0.174
Mean of Dep. Var.	0.432	0.393	0.251	0.162	0.111

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Insurance uptake (Cum.) is the sum of discount rates provided by the coupon over the three seasons prior to the interview. All specifications include individual-, insurance area-, survey year- fixed effects, adult equivalent, age, age-squared, female dummy, age and sex of the household head, number of children in the household.

Table A9: Impact on Child Activities using Balanced Panel

	Child Labor	Work FT	Work and School	School FT	No activity
	(1)	(2)	(3)	(4)	(5)
Insurance Uptake (Cum.)	-0.078*	-0.026	-0.092**	0.109***	0.042
	(0.044)	(0.033)	(0.039)	(0.035)	(0.026)
N	10445	10445	10445	10445	10445
F_{eff}	47.211	47.211	47.211	47.211	47.211
5% Critical Value	37.418	37.418	37.418	37.418	37.418
10% Critical Value	23.109	23.109	23.109	23.109	23.109
AR test p-val.	0.068	0.431	0.017	0.001	0.102
Mean of Dep. Var.	0.414	0.383	0.243	0.159	0.120

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Insurance uptake (Cum.) is the sum of discount rates provided by the coupon over the three seasons prior to the interview. All specifications include individual-, insurance area-, survey year- fixed effects, adult equivalent, age, age-squared, female dummy, age and sex of the household head, number of children in the household.

Table A10: Impact on Child Activities with Children who were 5-17 at baseline

	Child Labor	Work FT	Work and School	School FT	No activity
	(1)	(2)	(3)	(4)	(5)
Insurance Uptake (Cum.)	-0.068	0.004	-0.104**	0.134***	-0.025
	(0.047)	(0.035)	(0.044)	(0.041)	(0.021)
N	8393	8393	8393	8393	8393
F_{eff}	47.964	47.964	47.964	47.964	47.964
5% Critical Value	37.418	37.418	37.418	37.418	37.418
10% Critical Value	23.109	23.109	23.109	23.109	23.109
AR test p-val.	0.137	0.917	0.017	0.001	0.238
Mean of Dep. Var.	0.492	0.462	0.317	0.196	0.023

Notes: Standard errors, clustered at household level, are in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Insurance uptake (Cum.) is the sum of discount rates provided by the coupon over the three seasons prior to the interview. All specifications include individual-, insurance area-, survey year- fixed effects, adult equivalent, age, age-squared, female dummy, age and sex of the household head, number of children in the household.