The Effect of Microinsurance on Child Work and Schooling

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Abstract

I 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. I find insurance increases periodic herd migration, which could explain a decrease in children's work as a secondary activity since the herd migration increases schooling costs. I also find heterogeneity across age, birth order, and gender of a child suggesting stronger benefit of the insurance towards younger children and highlighting the difference between nature of girls' and boy's work.

JEL Classifications: G52, I20, J22, O15

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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). Policy responses to decrease child labor are often related to poverty reduction, where an increase in household income level is the key focus. However, the vulnerability of the poor households also stems from the high variability of their income. They have weak risk-coping strategies, so they are more susceptible to adverse income shocks such as droughts, floods, animal/crop disease, or illnesses. Such shocks are barriers to human capital accumulation among poor households by increasing child labor and decreasing child schooling and learning (Beegle, Dehejia, and Gatti, 2006; Björkman-Nyqvist, 2013; Bandara, Dehejia, and Lavie-Rouse, 2015; Shah and Steinberg, 2017; Koohi-Kamali and Roy, 2021; Park, Behrer, and Goodman, 2021).

Access to capital markets such as credit or insurance can mitigate such impacts of the adverse shock on children's work participation and schooling (Beegle, Dehejia, and Gatti, 2006; Alvi and Dendir, 2011; Bandara, Dehejia, and Lavie-Rouse, 2015), but conventional insurance products are not readily accessible for poor households due to their high implementation cost. As an alternative, index insurance has received much attention due to its lower cost in actuarial data collection and claims validation (Jensen and Barrett, 2017). Since the index is exogenous to any individual's production strategy, there is a lower probability of moral hazard or adverse selection at the household level than conventional insurance products. Greatrex et al. (2015) reports that the number of households insured by index insurance products is over millions worldwide.[1] However, there is scant evidence on the effect of index insurance on children's work and schooling decisions.

I examine the effects of index-based microinsurance uptake on children's participation in work and schooling. I use Index-Based Livestock Insurance (IBLI), launched in Arid and Semi-Arid Lands (ASAL) of Northern Kenya and Southern Ethiopia, targeting pastoral households comprising most of the region's population.[2] For identification, I exploit the insurance premium variation generated by the randomized discount rates. Specifically, I instrument the cumulative IBLI uptake with cumulative discount rate, which I will discuss later in detail. I investigate both the average effects of the insurance uptake across drought and non-drought periods first, and analyze disag-

[1] Over 30 million farmers are insured in India through national index insurance programs, nearly 200,000 farmers in East Africa (Kenya, Rwanda, and Tanzania) through the Agriculture and Climate Risk Enterprise (ACRE), over 20,000 smallholder farmers in Ethiopia and Senegal through the R4 Rural Resilience Initiative, and more than 15,000 nomadic herders in Mongolia through Index-Based Livestock Insurance Project (IBLIP).

[2] For the details of the product design, please refer to Chantarat et al. (2013).

gregated effects across periods to examine if child activity changes during the drought periods and whether the insurance is able to mitigate the effect. I also study how the effects operate by examining related household outcomes such as herding strategies, herd size, household income, and other risk coping strategies.

Arid and semi-arid lands of Northern Kenya and southern Ethiopia are well-suited to study the effects of IBLI on children's work and schooling. Pastoral livelihood systems are dominant in these areas, with low educational attainment and high child labor rates. Livestock herding is one of the income sources for 74 percent of the sample households, and 87 percent of the households have at least one of the household members engaged in livestock-related activities as their primary or secondary activity. Lybbert et al. (2004) showed that there exist multiple herd sizes equilibria, where households below a critical herd size threshold (typically in the range of 10-20 tropical livestock units (TLU)[3]) are trapped in a low-level equilibrium poverty trap. Then, catastrophic livestock losses triggered by droughts drive these pastoral households in the regions into poverty traps. Considering the median herd size of the sample is 8.5 TLU, the region has a substantial portion of the population at the risk of being trapped in poverty. Seasonal migration is critical in sustaining the herd size, considering spatio-temporal variability in forage and water access (Chantarat et al., 2017). However, the mobile nature of the pastoral livelihood and the remoteness of the region make the supply of education to these regions difficult. Due to an imperfect 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 other areas.

The primary data source of this paper 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 part of the pilot program implemented to encourage the uptake of the insurance product and evaluate the welfare effects of the insurance. As part of the program, local insurance companies collaborated with researchers at the International Livestock Research Institute (ILRI), randomly provided discount coupons to households with varying discount rates every sales season, and collected survey data. In addition, I use administrative data from the insurance company on insurance uptake.

The empirical strategy relies on the exogenous variation of insurance premiums paid by the households. The randomization was conducted every sales season, occurring twice a year, providing within-household variation in insurance premiums. We estimate the effect of insurance on child

[3]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

activities exploiting this exogenous variation – the discount rate – as an instrument for insurance uptake. The panel survey measured the children's activity choices annually while both insurance promotion activities with discount coupons and insurance purchase decisions occurred biannually. Moreover, the insurance coverage period is a year for each purchase. Therefore, I use cumulative insurance uptake incidents over the last three periods as the explanatory variable and cumulative discount rates over the same periods as an instrument. To ensure the validity of the instrument, I show that the insurance premium discount rate was uncorrelated with a range of household and individual characteristics, and the instrument has strong predictive power of the insurance uptake in the first stage.

The main finding is that IBLI shifts children's activities from work to schooling. The probability of a child engaged in child labor decreased by 8.5 percentage points and simultaneously working and going to school by 10.1 percentage points, while the probability of a child being a full-time student increases by 12.2 percentage points. Children decreasing work and increasing schooling as a secondary activity are the drivers of the effect.

I also find that the insurance helps children avoid being drawn to work with adverse weather shocks. Children from uninsured households are more likely to be engaged in child labor in drought seasons by 9.6 percentage points than non-shock seasons. However, the child labor of insured households during the drought seasons does not differ substantially from non-shock seasons.

In explaining the mechanisms, I investigate the effects on household-level outcome variables relevant for pastoral production and child activities, such as herding strategies and livestock holdings. First, I examine the effects on herding strategies such as herd mobility, livestock diversification, and livestock-related expenditure. I find that the insured households increase herd mobility and spending on livestock food during the non-drought periods, while there is no evidence of less livestock diversification among insured households. Since herd mobility increases the cost of schooling, children whose primary activity is to go to school and the secondary activity is work may decrease work participation. Livestock holding to increase among uninsured households during drought periods, but it does not explain the increase in children's work participation during drought periods among uninsured households. It is because such increase is concentrated among the households with large initial herd sizes, and the children's activities do not correspondingly follow such a pattern.

The effects are heterogeneous by age, birth order, and gender. First, younger children benefit more from insurance. Younger-age children (age 5-12) experience a statistically significant decrease in child labor, while older children (age 13-17) decrease participation in part-time work and schooling on average. Older age children from uninsured households are more likely to increase full-time work and work as a primary activity during drought periods, while no such increase can be found among younger children. However, none of these differences are statistically significant. A similar but more salient pattern arises between siblings. While younger siblings decrease child labor, full-time work, and work as a primary activity, the oldest siblings decrease part-time work and schooling on average. The differences are statistically significant, which shows that the firstborns bear the burden to support their younger siblings. Heterogeneity by gender reveals that the effects are similar across gender on average except for child labor. Girls decrease child labor by 12.6 percentage points, while boys do not experience a statistically significant decrease in child labor. Moreover, I find that girls increase their participation in work during droughts when the households are not insured, although the insurance mitigates such an increase. However, the effects are concentrated on a boys' shift from part-time work and schooling to full-time schooling.

This paper contributes to the growing literature on the effects of index insurance by adding rare evidence on the inter-generational effect of index insurance. Several studies find that index insurance can help invest in high-risk, high-return production strategies, shield households from adverse shocks that may drive them into a poverty trap, and improve the welfare of the insured household (Barnett, Barrett, and Skees, 2008; Dercon and Christiaensen, 2011; Karlan et al., 2014; Jensen and Barrett, 2017; Jensen, Barrett, and Mude, 2017; Janzen and Carter, 2019; Tafere, Barrett, and Lentz, 2019). However, there is little evidence on the effect of index insurance on children of the insured household. To my knowledge, this paper is the first to study the relationship between index insurance and children's work and schooling, as well as the mechanism through which any effects operate.

My findings also add evidence to the literature on the effect of weather shock on children's work and schooling. The existing literature finds that the household income shock induced by adverse weather shock, including droughts and floods, increases child labor and decreases schooling. These studies also find that access to credit or having more assets mitigate the adverse effects on human capital investments on children (Beegle, Dehejia, and Gatti, 2006; Björkman-Nyqvist, 2013; Bandara, Dehejia, and Lavie-Rouse, 2015; Shah and Steinberg, 2017; Koohi-Kamali and Roy, 2021). A few recent papers showed that the positive weather shocks that lead to increased household income could increase children's work participation and decrease schooling due to an increase in the opportunity cost of children's schooling (Shah and Steinberg, 2017; Nordman, Sharma, and Sunder, 2021). This paper adds another evidence to the literature that adverse weather shock negatively affects children's participation in work and schooling. It also shows that having access to formal insurance products, rather than credit or the alternative insurance scheme such as assets, also mitigates such effects.

Lastly, this paper expands the literature on the relationship between insurance and children's work and schooling. A few existing studies find that health insurance decreases children's work and increases educational attainment by protecting households from shocks to adult labor (Landmann and Frölich, 2015; Frölich and Landmann, 2018; Guarcello, Mealli, and Rosati, 2010). Index insurance differs from health insurance since it directly decreases uncertainty over income, not a factor of production. It also differs in the sense that the first-order effect of the insurance is a change in the investment strategies, which could lead to an increase in productive assets. Studies on the relationship between child labor and a household's productive assets show that child labor complements productive assets (Basu, Das, and Dutta, 2010; Edmonds and Theoharides, 2020). By showing that index insurance shifts children's activities from work and schooling to schooling only, this paper shows that ensuring income stability increases investment in children's human capital.

The results have implications for social policy as well. First, index insurance can be promoted as a social protection policy in low- and middle-income countries, which recently received growing attention. This paper suggests that index insurance can contribute to long-term economic development by inducing human capital accumulation among insured households. Secondly, the child labor reduction policy has focused on supporting household income directly or through providing productive assets to utilize. This paper shows that subsidizing index insurance could be a good way to complement the existing child labor reduction policies since index insurance allows 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 analytically ambiguous. A pastoral household produces livestock-related products such as milk, meat, or traded livestock. Inputs used to produce these outputs include labor, fodder, and livestock. Here, consider livestock as capital which is a source of input and 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.[4]

Since the labor market for children is close to nonexistent, children's work is restricted to within-

[4] Note that a child can allocate her time to both work and schooling, leading to participation in both activities.

household tasks. For children in pastoral households, livestock-related work is a strong candidate for within-household tasks. Types of livestock-related work children are involved in include animal herding, feeding the animals kept at the main base camp, milking the lactating animals, or selling livestock-produced goods. Male children are more likely to herd animals once they become a certain age. Children's work is a complementary input to the herd size, but the wealthiest households who could afford hiring herders may choose to employ herders instead of sending children to work.

One of the important herding strategies is being transhumant (or herd mobility, i.e., taking the livestock to grazing land to feed animals). It is a beneficial strategy for both the long term and short term. While it increases the quantity of the animal feeding in the short-term, it maintains the grazing land condition at a sustainable level in the long term (Hurst et al., 2012). It often takes up to 3 months per trip, and it is not uncommon for children to accompany the herders on this trip. When they do, the cost of accessing school increases as they move to a different area.

The household enjoys its utility from consumption, leisure, and children's human capital. Children's time invested in schooling will increase their human capital. It leads to an increase in a household budget in future periods, thereby increasing the present value of the household utility. I assume both the credit and labor markets are not complete, so 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 time spent on schooling.

IBLI insures the livestock loss due to droughts in the area. Therefore, it affects multiple aspects of pastoralists' livelihood, including herding strategies, herd size, and the income from livestock rearing. With this in mind, I can hypothesize the direction of the effects of 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 from 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 that 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 child labor.

IBLI could also work through income. It increases income per adult equivalent[5], 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 domi-

[5] 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.

nant. Within the 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.[6] On the 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 pastoral 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 pastoral 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 pastoral households. Both male and female children in a pastoral household are important labor forces for the family's livelihood. In Kenya, 13 percent of

[6]These numbers are calculated by the author using the publicly available household survey. I use Kenya Integrated Household Budget Survey 2015-2016 was for Kenya and Socioeconomic Survey 2015-2016 for Ethiopia.

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 pastoral 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)[7]. 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 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 the study areas work more intensely than the other parts of the country.

A higher intensity of child labor in the study areas is related to the fact that most households in the study area are pastoralists. Within the study 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).[8] The distribution at the household level looks similar, which I 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. 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

[7]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.

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

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 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 the study 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

I use two main data sources for the empirical analysis. 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, I 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.[9] I also use a measure of a child's 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, I 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. I subtract hours spent on work and schooling from 24 hours to compute hours spent on neither work nor schooling.

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.

I restrict the study sample to children aged 5 to 17 for the analysis for several reasons. First, it is common in the literature on child labor to study children aged 5 to 17. Secondly, I consider the two country's minimum legal working age. Ethiopia's minimum legal working age was 14 before,

[9] 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.

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, I 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

I 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 the study sample had access to the insurance. The purchase of the insurance is thus inherently endogenous, and I 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, I instrument insurance coverage with a premium discount provided by randomly distributed coupons, following Jensen, Barrett, and Mude (2017).

As the first stage, we estimate:

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

where $CIBLI_{hrt}$ denotes the cumulative insurance uptake of the household h in region r covering the period t, and $DChrt$ denotes the cumulative discount rate over the same sales seasons. Insurance uptake 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, my preferred specification is the one using the insurance uptake. Cumulative insurance uptake is the total number of insurance uptake 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.[10] Figure A2 presents the distribution of cumulative discount rates and insurance uptake 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-, 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), I 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, I 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, I 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 the study period, droughts occurred in two sales seasons in Marsabit and one in Borena. Using this information, I also estimate the effect of insurance when the drought shock hits the

[10] 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.

region. As the first stage, I 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, the 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, the estimates of the insurance effect on child outcome capture the average of the household's response to the shock and to the payouts.

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

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

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

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 I 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 the 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, I 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.I 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. I 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}. I 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 Olea and Pflueger (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. I 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. I present Kleibergen-Paap rk Wald F-statistic, as a complementary measure of a first stage predictive power. I 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. I 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 uptake on children's activity choices

I first examine the average effect of insurance on children's activity choices. Child labor, full-time work, part-time work and schooling, full-time schooling, and neither work nor schooling were used as a series of indicators for children's activities. Child labor is an indicator for more intensive engagement in work, and the remaining four categories are mutually exclusive, and covers children's activities comprehensively.

I find that the insurance uptake over the past year decrease the probability of children's participation in child labor, part-time work and schooling, and increase full-time schooling. The results presented in Panel A of Table 3 show that for an additional insurance uptake experience over the three past seasons, the probability of child labor decreased by 8.6 percentage points, part-time work and schooling by 9.8 percentage points, and full-time schooling increases by 11.9 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 20.1 percent, part-time work and schooling by 36.1 percent, and full-time schooling by 75 percent. The average insurance uptake rate covering one year is about 32 percent, so the actual effect is smaller. But this is a substantial change in children's activity choices.

On the other hand, the effect on the probability of working full-time is estimated to decrease by 2 percentage points, and the probability of participating in none of the activities is estimated to increase 0.5 percentage points, 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.

I disaggregate the average effect to the effects during the drought and non-drought periods. The estimated impact presented in Panel B of Table 3 first reveals that shift of children's activity choice from part-time work to full-time schooling was driven by the effects in non-drought periods. The estimates presented in the second row of each panel show results consistent with that of Panel A: children from the insured households during non-drought periods decrease part-time work and schooling by 8.7 percentage points and increase full-time schooling by 10.9 percentage points. The estimates are statistically significant at 10 and 1 percent level, respectively. 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 9.1 percentage points. It is 17 percent increase, which is large in magnitude. However, the insurance offsets the increase in child labor – the coefficient on $Shock \times Uptake$ is -0.198, 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 I can reconcile this result using the effects on children's working hours presented in Table A3. It shows that working children increase hours spent on work upon shock without insurance, supporting the finding on child labor.

To complement the lack of appropriate 1st stage F-statistics and ensure that the estimates are not threatened by the weakness of the first stage estimates, I repeat the estimation in Panel B of Table 3 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 uptake 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 I showed that the predictive power is strong enough for the endogenous variable without the interaction with the shock indicator, I confidently present that the estimates do not suffer from the weak instrument problem.

Using how the activities were classified, I 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 19.5 percentage points. Consistently, insurance uptake increases schooling as a secondary activity by 3 percentage points. Moreover, Panel B shows that the effects on secondary activities are concentrated in the insured households in non-drought periods, which is also consistent with the results from 3. Considering only 2.5 percent of the children working and going to school simultaneously responded that they work as a primary activity and go to school as their secondary activity, the decrease in work as a secondary activity is consistent with the shift from part-time work and schooling to full-time schooling.

I cannot reject the hypothesis that the insurance uptake did not affect the work as a primary activity. None of the primary activities were affected substantially by IBLI on average. However, I find additional supporting evidence of IBLI protecting children from increasing work participation upon drought shock. The results in Panel B show that children from uninsured households increase their participation in livestock-related work[11] as their primary activity increases in drought periods by 5.5 percentage points. The estimate is statistically significant at a 5 percent level. I confirm that the children from insured households, on the other hand, do not experience an increase in livestock-related work participation.

6.2 Potential Mechanisms

The previous subsection presented two main findings about the effect of IBLI on children's activities: 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, I examine the effects on household outcomes including herding strategies, expenditure, and livestock holding. Since effects during the non-shock periods drive the average effects are driven, I examine the disaggregated effects in this subsection. Relevant average effects are reported in the Appendix.

Herd mobility is an important herding strategy for households which affects the cost of children's schooling. I 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 mobility focuses on whether a household is mobile, the share of kept away livestock is the intensity of the herd 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 simultane-

[11] 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.

ously 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 months, 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 cope with drought risks. I measure diversification in two ways – Simpson's diversification index[12] for livestock and income sources. I find that both measures show no substantial changes in livelihood diversification.

In addition, I observe an increase in livestock-related expenditure during the non-shock periods. Table 6 shows that 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 livestock production, which is consistent with the findings of Jensen, Barrett, and Mude (2017). An increase in livestock expenditure is associated with higher share of full-time schooling children, which is consistent with the previous finding of increased full-time schooling among children from insured households.

Moreover, the increase in livestock expenditure among insured households during non-drought periods is consistent with Karlan et al. (2014) since the food for livestock (a risky input) has higher marginal returns during the good season (non-shock periods). The fact that none of the children's work activities increase among insured households during non-drought periods indicates that even though labor input is typically considered as a risky input, we need to consider child labor differently. Even when the productivity of a risky input increases, children's labor may not be utilized if it accompanies a significant increase in changes in production strategies that leads to higher schooling cost.

Another potential channel is livestock holding. Estimates presented in Table 7 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. I further examine the heterogeneous effects of shock and insurance across initial herd sizes: I divided the sample into quintiles using the herd size at baseline and estimated the effects within each group. The results presented in Panel A of Table 8 show that the increase in herd size is driven by the households from the top quintile of the distribution. It indicates that the households with largest herd size at baseline increase herd size upon drought to use the arbitrage. In fact, households with the lowest quintile herd sizes decrease herd size during

[12] Simpson (1949) introduced the index to measure the degree of concentration. In economics literature, Hirschman (1964) uses the formula to measure market concentration. Here, I subtract the sum of square of the share of each animal out of the animals owned (or the share of income from each income source out of the total household income), to obtain a measure of diversity, instead of concentration.

the drought periods when they are not insured. However, the results presented in Panel B show that children from all quintiles seem to increase participation in livestock related tasks during drought periods without insurance. Therefore, an increase in child labor and livestock-related tasks during drought periods among uninsured households is another evidence of using children as a means of self-insurance.

6.3 Heterogeneity of the Effects

I 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 average effects are not statistically different between the younger age group (5-12 years old) and older age group (13-17 years old). However, the estimates suggest that the younger children experience decreases in more intensive activities. Both age groups increase full-time schooling, but younger age group decreases participation in child labor, while older age group decreases the part-time work and schooling. Panel B and C shows this more prominently. Younger age group are 10.5 percentage points more likely to be engaged in child labor during droughts if they are not insured, but insurance mitigates this probability by 24.3 percentage points, estimated at 10 percent significance level. While they also decrease participation in work as a secondary activity during non-drought periods, it does not lead to decrease in part-time work and schooling.

However, the magnitude of a decrease in work as secondary activity in non-drought periods is larger for the older age group, and thus a substantial decrease in part-time work and schooling for these children. But it is clear that the older age group is more easily utilized when a household face drought shock. They are more likely to increase child labor, full-time work, work as a primary activity and decrease full-time schooling during droughts without insurance. However, as consistent with previous findings, insurance mitigates these adverse effects on older age group children during droughts. During non-drought periods, while insurance decrease older-age children's part-time work and schooling and increase full-time schooling, it also increases older age children's work as a primary activity by 10.2 percentage points, statistically significant at 10 percent level.

A similar but more evident pattern arises in the heterogeneity by birth order presented in Table 10. All children increase participation in full-time schooling on average. However, the oldest sibling only decreases part-time work and schooling while the younger ones decrease child labor, full-time work participation, and work as a primary activity. The difference in these variables across the two groups is statistically significant (Panel A). Panel B and C shows the same pattern during non-drought periods, and that the first-borne child without insurance increases their participation in work during drought periods, although it is mitigated substantially by insurance.

The average effects are statistically similar between genders in general, but disaggregated effects show that boys decrease their work during non-drought periods while girls during drought periods due to insurance. Table 11, Panel A shows that both genders switched from part-time work and schooling to full-time schooling, and none of the average effects and statistically significant. The magnitude of a decrease in child labor was much higher among girls – they decrease child labor by 11.9 percentage points, which is statistically significant at 5 percent level, while boys did not substantially. 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 shows a more stark difference. During drought periods, girls increase participation in work (child labor, part-time work and schooling) and decrease full-time schooling substantially, all of which were mitigated by insurance. On the other hand, boys shifted from part-time work and schooling to full-time schooling during non-drought periods, and did not show any substantial changes during drought periods.

6.4 Robustness check

I check if the 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 the specification used for the analyses, the cumulative IBLI uptake measures the number of IBLI uptake over the three latest sales seasons due to the recall period of child outcomes. Therefore, past purchases 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 I show the estimates, including the cumulative past insurance uptake as a second endogenous variable. In this case, I cannot adequately test for the weaknesses of the instrument, so I focus on the estimated results. Table A8 shows that the 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 uptake, measured by Tropical Livestock Units. Table A9 shows the results are robust to a different measure of insurance coverage. It also shows that not only at the extensive margin of insurance uptake, but also at the intensive margin of insurance has effect on children's activity choices. The results suggest that an additional TLU of livestock insured decreases child labor by 1.7 percentage points, part-time work and schooling by 1.9 percentage points, and increase full-time schooling by 2.3 percentage points.

Although the two regions – Marsabit district and Borana zone – are adjacent areas sharing pastoral livelihood, children from these two areas are different in school enrollment. In Marsabit district, children listed schooling as their primary or secondary activity was 58 percent, while it was only 34 percent in Borana zone. Work engagement is lower in Marsabit district. 68 percent of Marsabit children indicated the engagement in work while it was 77 percent in Borana zone. Child labor was higher in Borana zone (64 percent), compared to that of Marsabit district (38 percent). While I include individual fixed effects and area (sub-region) fixed effects to control for time-invariante country-specific characteristics, the year-specific situations within a country could have separate effects. Therefore, we include country $\times$ year fixed effects in the analysis as a robustness check. By including country $\times$ year fixed effects, I may absorb the variations necessary to identify the effects. Results presented in Table A10 show the qualitatively the same story as the main results, while the size of the coefficients become smaller and the estimates become not statistically significant anymore. Specifically, the table shows that child labor decreases by 9.2 percentage points on average. A shift from part-time work and schooling to full-time schooling (i.e., negative coefficients on part-time work and schooling and positive coefficients on full-time schooling) can be found, but the estimates are not statistically significant.

Lastly, I 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 my results do not come from a sample composition. Table A11 and A12 shows that this is not the case, and the 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 within the household and a limited supply of quality education, children from drought-prone pastoral communities are exposed to child labor and low school enrollment. Index-Based Livestock Insurance (IBLI), designed to protect the welfare of the household from such adverse shocks, has potential to address this concern of low investment in children's human capital. However, such effects are not well understood. This paper fill this gap in the literature using the exogenous variation in the price of IBLI, 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, I find that insurance increases households' investment in children's human capital. Children decrease participation in child labor and part-time work and schooling and increase full-time schooling on average.

Moreover, we confirm that pastoral households increase child labor and livestock-related work as children's primary activities during drought periods as a self-insurance measure, and that insurance prevents the usage of children as self-insurance from occurring. The effects are robust to various specifications and sample restriction criteria. I find that the effects are driven by the changes in herding strategies, specifically.

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. In addition, while I do not find statistically significant differences of the effects across gender, I 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 results suggest that income stabilizing policies such as index insurance can increase human capital investments for children. Therefore, it highlights that supporting financial markets in low-income countries can complement poverty reduction programs focusing on income growth. These findings correspond to the literature that access to credit mitigates the adverse effects of covariate shock on children's human capital investments (Beegle, Dehejia, and Gatti, 2006; Landmann and Frölich, 2015; Bandara, Dehejia, and Lavie-Rouse, 2015; Shah and Steinberg, 2017). This paper adds that decreased variability of household income can increase human capital investment even in the absence of covariate shock.

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

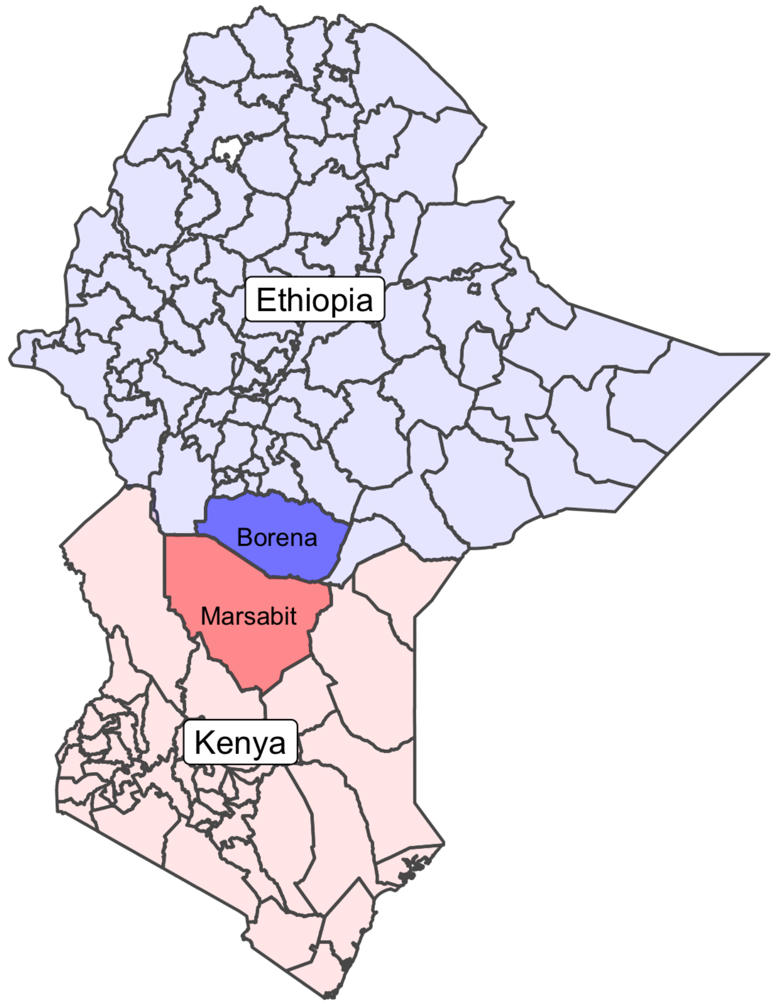
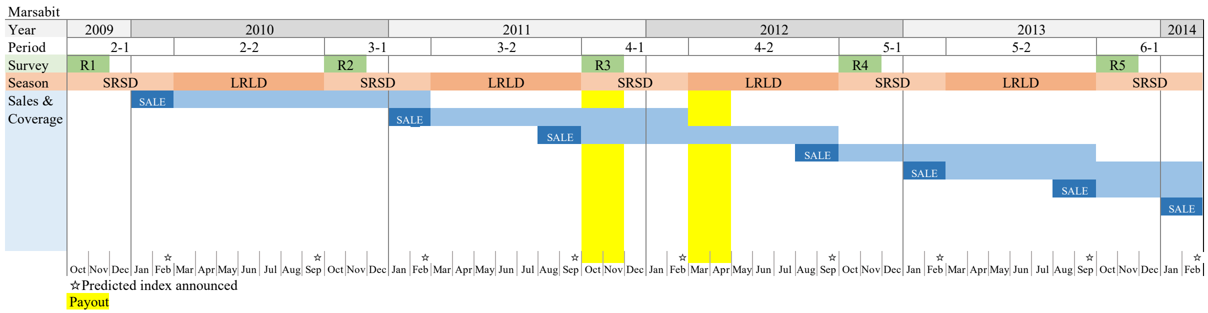


Figure 2: Timeline of the projects

(a) Marsabit District, Kenya



(b) Borena Zone, Ethiopia

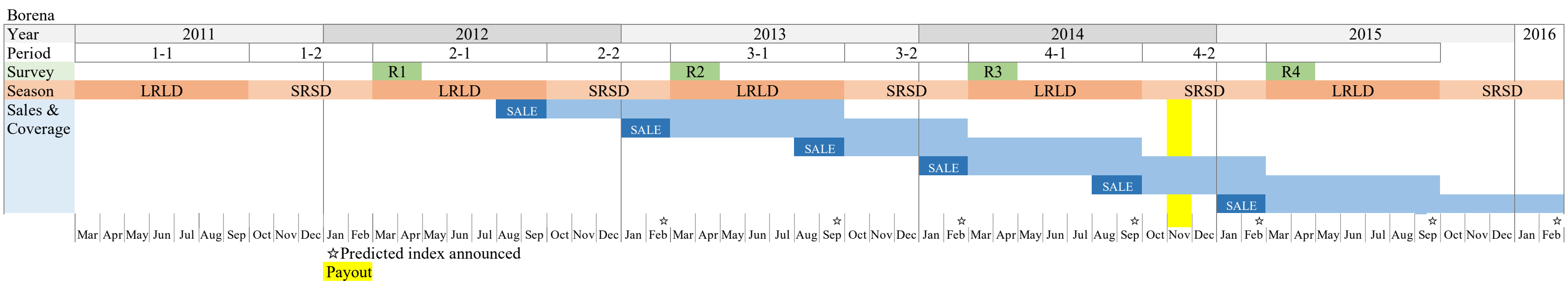
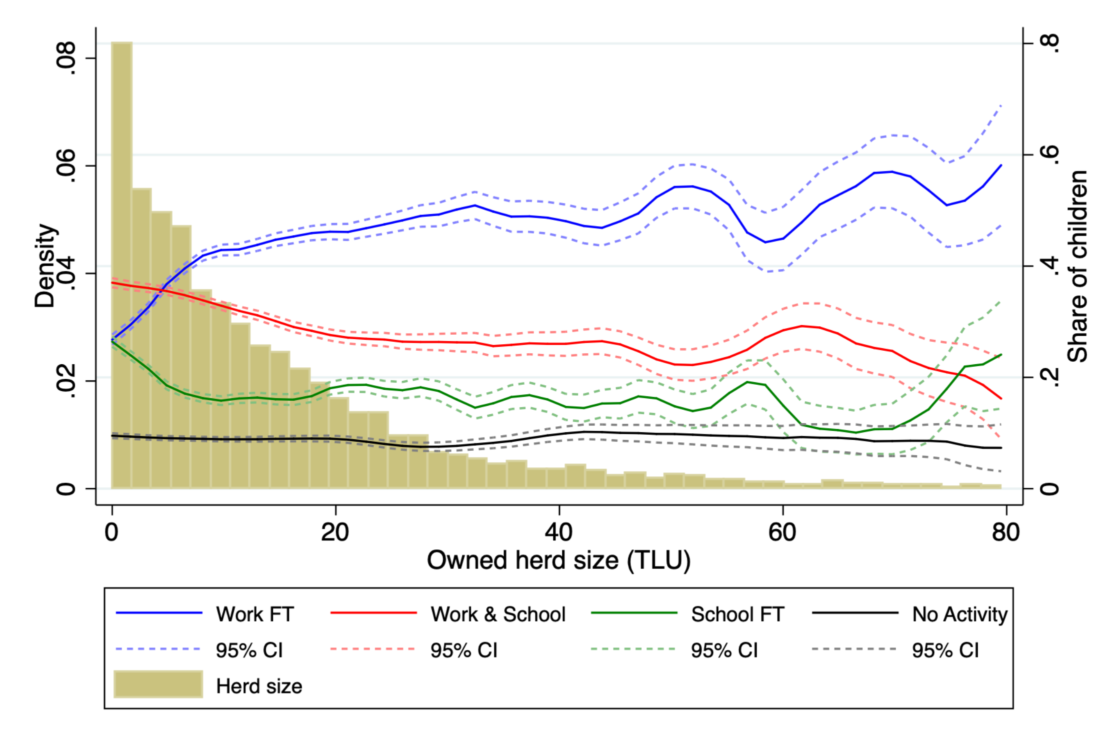


Figure 3: Children's activity by herd size

(a) Participation



(b) Hours, equals to zero if not participating

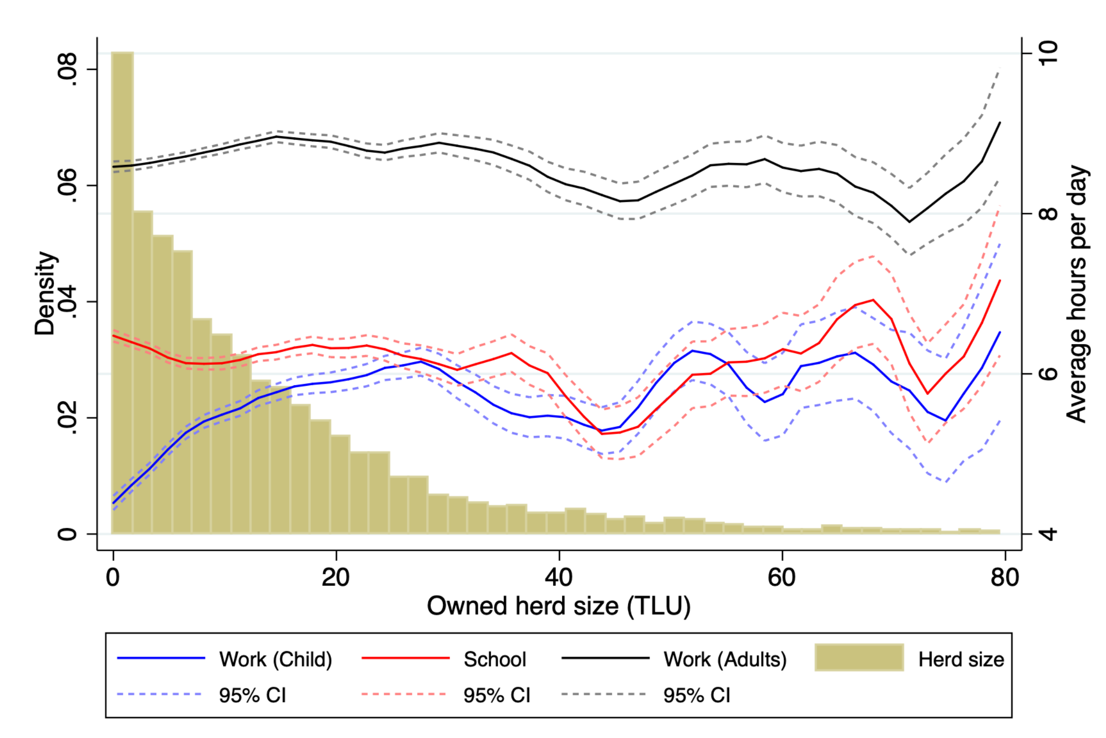
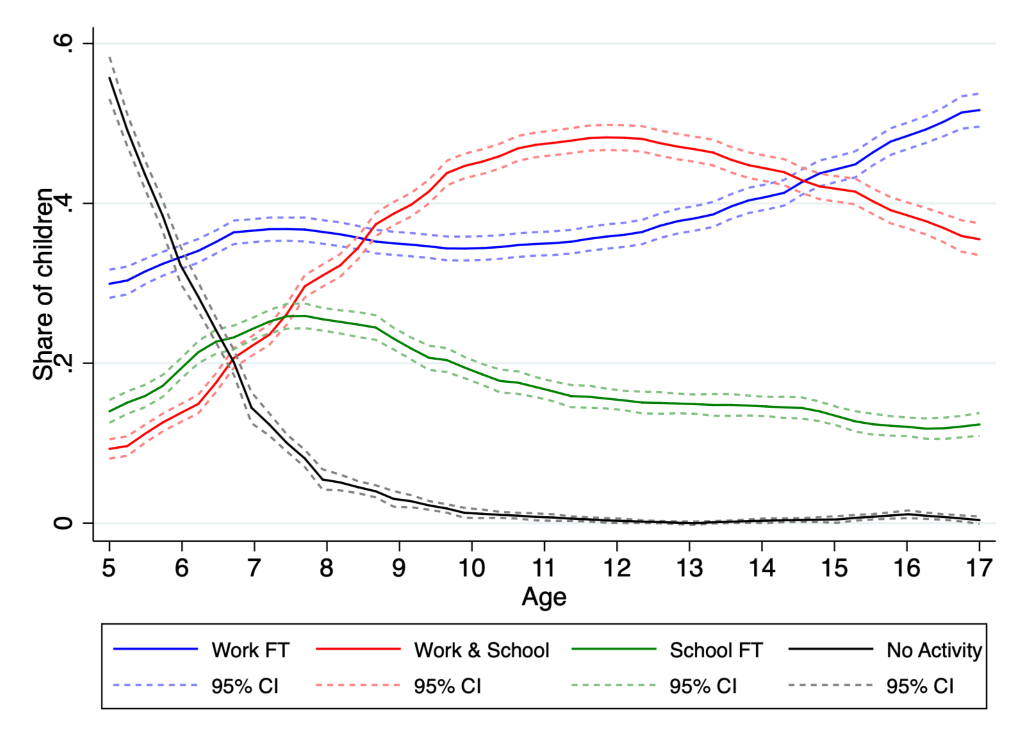


Figure 4: Children's activity by age and gender

(a) Girls



(b) Boys

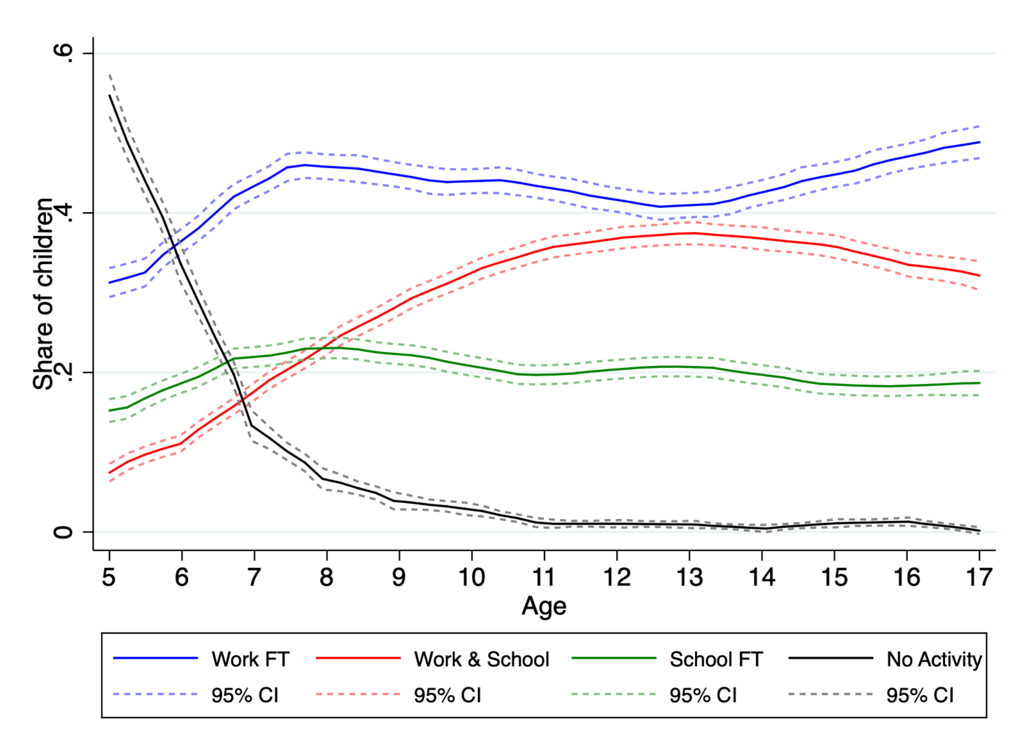
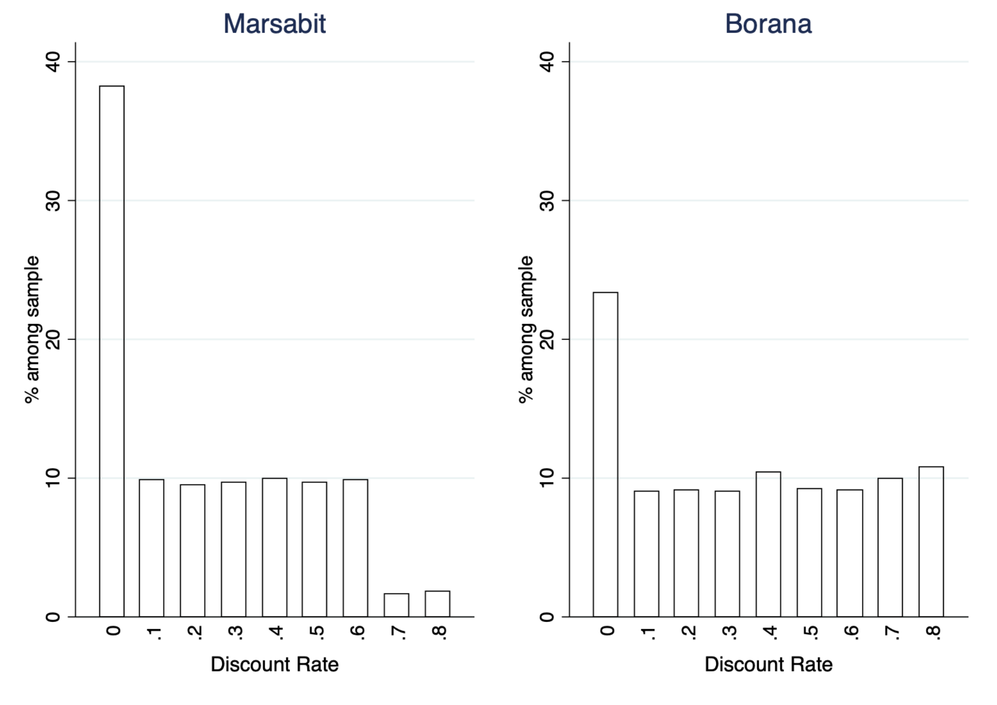


Figure 5: Discount Rate and Insured Livestock

(a) Discount Rates



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

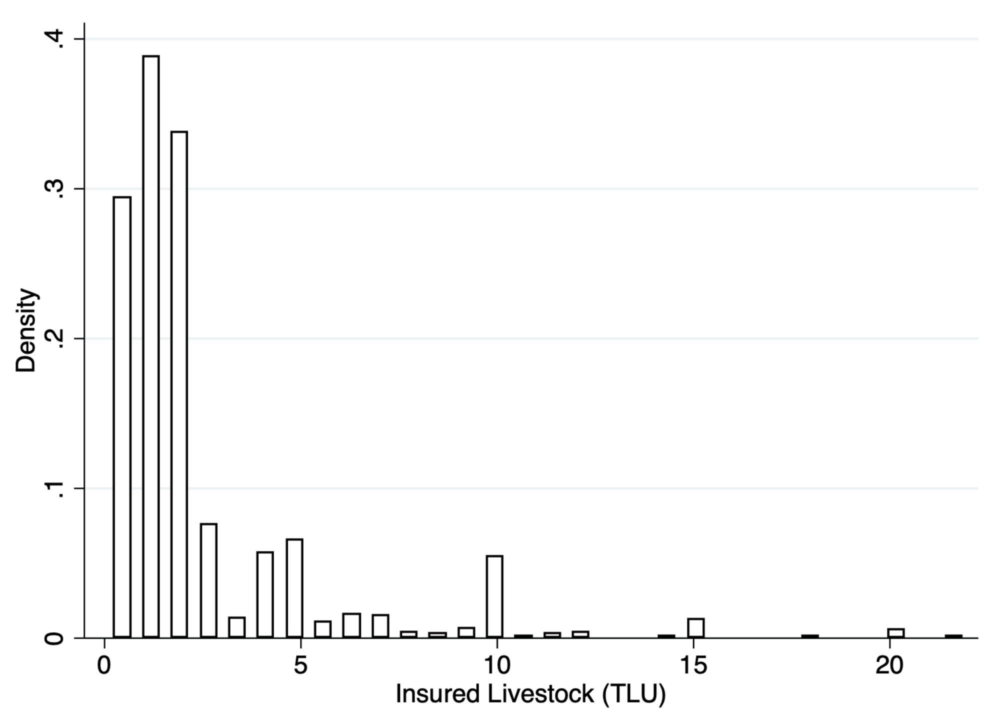


Table 1: Balance between recipients and non-recipients of coupon

	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 × Insurance Uptake (Cum.)	Insurance Uptake (Cum.)
	(1)	(2)	(3)
Discount rate (Current + Cum.)	0.333***	0.048***	0.362***
	(0.031)	(0.011)	(0.030)
Shock × Discount rate (Cum.)	0.001	0.003***	
	(0.001)	(0.001)	
N	11319	11319	11319

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	Neither Work Nor School
	(1)	(2)	(3)	(4)	(5)
Panel A: Average Effects					
Insurance Uptake (Cum.)	-0.086**	-0.025	-0.098***	0.119***	0.005
	(0.042)	(0.032)	(0.037)	(0.034)	(0.025)
N	12243	12243	12243	12243	12250
F_{eff}	54.577	54.577	54.577	54.577	54.581
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.	0.036	0.427	0.008	0.000	0.854
Mean of Dep. Var.	0.426	0.374	0.271	0.163	0.193
Panel B: Disaggregated Effects					
Shock	0.091**	0.014	0.036	-0.028	-0.022
	(0.040)	(0.022)	(0.035)	(0.036)	(0.018)
Insurance Uptake (Cum.)	-0.034	-0.018	-0.087*	0.109***	-0.004
	(0.053)	(0.043)	(0.046)	(0.042)	(0.034)
Shock × Insurance Uptake (Cum.)	-0.198*	-0.028	-0.056	0.046	0.039
	(0.102)	(0.066)	(0.089)	(0.090)	(0.054)
Shock+Uptake × Shock (coef.)	-0.108	-0.014	-0.020	0.018	0.017
Shock+Uptake × Shock (p-val.)	0.140	0.783	0.756	0.774	0.685
N	11319	11319	11319	11319	11326
K-P F-stat	23.929	23.929	23.929	23.929	23.917
AR test p-val.	0.007	0.591	0.025	0.002	0.685
Mean of Dep. Var.	0.535	0.406	0.314	0.180	0.100

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.)	0.009	0.014	0.001	-0.007	-0.195***	-0.068*	-0.083*	0.030**
	(0.033)	(0.030)	(0.028)	(0.029)	(0.053)	(0.038)	(0.044)	(0.013)
N	12242	12242	12242	12242	12243	12243	12243	12243
F_{eff}	54.509	54.509	54.509	54.509	54.577	54.577	54.577	54.577
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.	0.780	0.644	0.975	0.818	0.000	0.072	0.052	0.017
Mean of Dep. Var.	0.376	0.252	0.105	0.429	0.398	0.121	0.249	0.005
Panel B: Disaggregated Effects								
Shock	0.026	0.055**	-0.026	-0.004	0.046	-0.036	0.062	0.031***
	(0.022)	(0.022)	(0.020)	(0.022)	(0.047)	(0.028)	(0.044)	(0.010)
Insurance Uptake (Cum.)	0.025	0.036	-0.005	-0.012	-0.193***	-0.068	-0.089*	0.040**
	(0.044)	(0.042)	(0.036)	(0.037)	(0.067)	(0.050)	(0.053)	(0.018)
Shock $\times$ Insurance Uptake (Cum.)	-0.058	-0.096	0.035	0.015	-0.038	0.027	-0.032	-0.048
	(0.063)	(0.067)	(0.056)	(0.061)	(0.126)	(0.072)	(0.111)	(0.032)
Shock+Uptake $\times$ Shock (coef.)	-0.032	-0.041	0.010	0.011	0.007	-0.009	0.030	-0.017
Shock+Uptake $\times$ Shock (p-val.)	0.511	0.420	0.818	0.809	0.936	0.866	0.702	0.485
N	11318	11318	11318	11318	11319	11319	11319	11319
K-P F-stat	23.961	23.961	23.961	23.961	23.929	23.929	23.929	23.929
AR test p-val.	0.650	0.324	0.782	0.951	0.000	0.334	0.087	0.061
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	Livestock Diversity Index	Income Diversity Index
	(1)	(2)	(3)	(4)
Shock	-0.062	0.045	-0.019	0.015
	(0.048)	(0.037)	(0.021)	(0.031)
Insurance Uptake (Cum.)	0.241***	0.216***	-0.010	0.060
	(0.079)	(0.060)	(0.023)	(0.042)
Shock $\times$ Insurance Uptake (Cum.)	-0.127	-0.215**	0.058	-0.078
	(0.132)	(0.101)	(0.050)	(0.080)
Shock+Uptake $\times$ Shock (coef.)	-0.189	-0.170	0.038	-0.063
Shock+Uptake $\times$ Shock (p-val.)	0.056	0.024	0.273	0.275
N	4327	4145	4327	4327
K-P F-stat	25.486	24.784	25.486	25.486
AR test p-val.	0.002	0.000	0.503	0.358
Mean of Dep. Var.	0.600	0.633	0.409	0.215

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 Expenditures in Response to Shock

	Food expenditure	Non-food expenditure	Livestock expenditure (Total)	Livestock food	Livestock Veterinary
	(1)	(2)	(3)	(4)	(5)
Shock	-1.717*	-0.198	0.220	0.063	0.067
	(0.946)	(1.276)	(0.180)	(0.128)	(0.047)
Insurance Uptake (Cum.)	-1.318	0.832	0.433*	0.269**	-0.044
	(1.301)	(1.357)	(0.234)	(0.134)	(0.051)
Shock × Insurance Uptake (Cum.)	1.016	-3.362	-0.818	-0.480	0.011
	(2.488)	(2.906)	(0.498)	(0.388)	(0.135)
Shock+Uptake × Shock (coef.)	-0.701	-3.560	-0.597	-0.417	0.077
Shock+Uptake × Shock (p-val.)	0.692	0.073	0.105	0.130	0.416
N	4324	4317	4315	4315	4315
K-P F-stat	25.517	25.431	25.275	25.275	25.275
AR test p-val.	0.572	0.493	0.099	0.107	0.675
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
	(1)	(2)	(3)	(4)
Shock	2.630**	3.667***	2.002**	0.840
	(1.050)	(1.267)	(0.944)	(0.580)
Insurance Uptake (Cum.)	2.123	-0.054	-1.241	-1.367*
	(1.896)	(2.284)	(1.651)	(0.719)
Shock × Insurance Uptake (Cum.)	-4.021	-3.587	-1.800	-0.105
	(2.624)	(3.105)	(2.162)	(1.416)
Shock+Uptake × Shock (coef.)	-1.391	0.080	0.202	0.735
Shock+Uptake × Shock (p-val.)	0.458	0.970	0.890	0.442
N	4327	4327	4327	4327
K-P F-stat	25.486	25.486	25.486	25.486
AR test p-val.	0.297	0.372	0.317	0.107
Mean of Dep. Var.	13.507	14.772	9.783	3.972

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.)	-0.149***	-0.031	-0.072	0.099**	-0.006	-0.195***
	(0.057)	(0.046)	(0.046)	(0.041)	(0.047)	(0.063)
Age 13-17 × Insurance Uptake (Cum.)	-0.040	-0.000	-0.198***	0.180***	0.054	-0.268***
	(0.069)	(0.044)	(0.072)	(0.064)	(0.044)	(0.098)
Difference	-0.109	-0.031	0.127	-0.081	-0.059	0.073
	(0.087)	(0.064)	(0.081)	(0.071)	(0.064)	(0.108)
N	12243	12243	12243	12243	12242	12243
Panel B: Disaggreagted Effects, Children of Age 5-12						
Shock	0.105*	0.010	0.006	0.019	0.019	0.012
	(0.055)	(0.033)	(0.042)	(0.044)	(0.033)	(0.055)
Insurance Uptake (Cum.)	-0.087	-0.022	-0.050	0.085*	-0.003	-0.168**
	(0.071)	(0.062)	(0.055)	(0.050)	(0.063)	(0.077)
Shock × Insurance Uptake (Cum.)	-0.243*	-0.029	-0.058	0.018	-0.022	-0.077
	(0.142)	(0.092)	(0.105)	(0.110)	(0.095)	(0.145)
Shock+Uptake × Shock (coef.)	-0.137	-0.020	-0.053	0.037	-0.004	-0.065
Shock+Uptake × Shock (p-val.)	0.176	0.782	0.485	0.634	0.959	0.537
N	6883	6883	6883	6883	6883	6883
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	0.129**	0.048*	0.080	-0.126**	0.065**	0.095
	(0.057)	(0.025)	(0.062)	(0.062)	(0.026)	(0.076)
Insurance Uptake (Cum.)	-0.004	0.021	-0.217**	0.171**	0.102*	-0.303**
	(0.083)	(0.058)	(0.088)	(0.074)	(0.059)	(0.120)
Shock × Insurance Uptake (Cum.)	-0.192	-0.093	-0.004	0.115	-0.182**	0.032
	(0.139)	(0.073)	(0.157)	(0.154)	(0.077)	(0.201)
Shock+Uptake × Shock (coef.)	-0.064	-0.045	0.075	-0.011	-0.116	0.127
Shock+Uptake × Shock (p-val.)	0.518	0.427	0.497	0.920	0.054	0.386
N	3866	3866	3866	3866	3866	3866
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 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.)	-0.039	0.076	-0.222***	0.142**	0.133**	-0.340***
	(0.076)	(0.059)	(0.068)	(0.057)	(0.060)	(0.098)
Others × Insurance Uptake (Cum.)	-0.131***	-0.094**	-0.035	0.116***	-0.068*	-0.145***
	(0.051)	(0.040)	(0.039)	(0.038)	(0.040)	(0.056)
Difference	0.092	0.169**	-0.187**	0.027	0.200***	-0.195*
	(0.090)	(0.071)	(0.075)	(0.064)	(0.071)	(0.106)
N	12243	12243	12243	12243	12242	12243
Panel B: Disaggreagted Effects, Oldest siblings						
Shock	0.129**	0.046*	0.001	-0.019	0.070**	-0.023
	(0.054)	(0.027)	(0.048)	(0.049)	(0.028)	(0.058)
Insurance Uptake (Cum.)	0.098	0.122	-0.216**	0.124*	0.211**	-0.414***
	(0.103)	(0.087)	(0.090)	(0.075)	(0.087)	(0.134)
Shock × Insurance Uptake (Cum.)	-0.376**	-0.128	-0.014	0.052	-0.213**	0.172
	(0.150)	(0.101)	(0.136)	(0.137)	(0.094)	(0.181)
Shock+Uptake × Shock (coef.)	-0.247	-0.082	-0.013	0.033	-0.143	0.149
Shock+Uptake × Shock (p-val.)	0.035	0.344	0.904	0.750	0.076	0.301
N	3679	3679	3679	3679	3679	3679
K-P F-stat	0.535	0.406	0.314	0.180	0.412	0.446
Panel C: Disaggreagted Effects, Younger siblings						
Shock	0.040	-0.011	0.029	-0.003	-0.012	0.048
	(0.052)	(0.037)	(0.044)	(0.042)	(0.037)	(0.056)
Insurance Uptake (Cum.)	-0.131**	-0.100*	-0.049	0.128***	-0.087	-0.154**
	(0.066)	(0.056)	(0.049)	(0.047)	(0.056)	(0.072)
Shock × Insurance Uptake (Cum.)	-0.031	0.026	0.013	-0.030	0.061	-0.012
	(0.127)	(0.094)	(0.101)	(0.099)	(0.098)	(0.136)
Shock+Uptake × Shock (coef.)	0.010	0.015	0.042	-0.033	0.048	0.036
Shock+Uptake × Shock (p-val.)	0.914	0.823	0.545	0.630	0.497	0.701
N	6999	6999	6999	6999	6998	6999
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

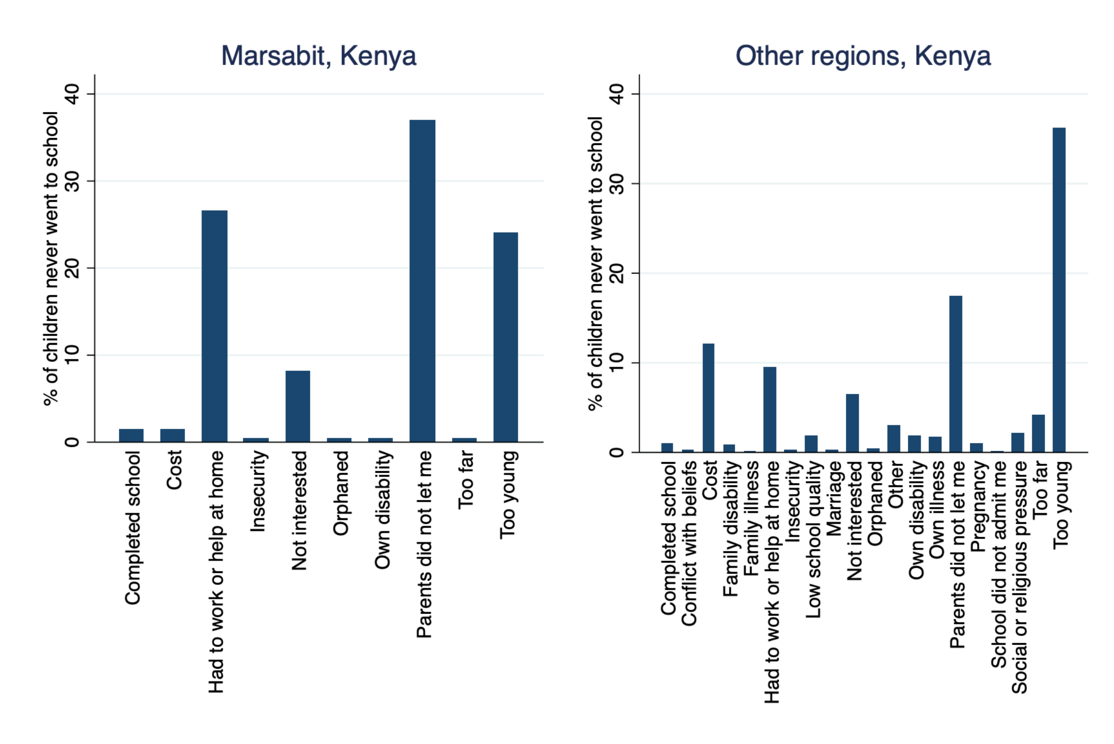
	Child Labor	Work FT	Work and School	School FT	Work as Primary	Work as Secondary
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Heterogeneity of Average Effects						
Female × Insurance Uptake (Cum.)	-0.119**	-0.039	-0.094*	0.099**	0.018	-0.176***
	(0.057)	(0.045)	(0.050)	(0.040)	(0.047)	(0.067)
Male × Insurance Uptake (Cum.)	-0.054	-0.015	-0.100**	0.141***	-0.004	-0.211***
	(0.058)	(0.043)	(0.050)	(0.051)	(0.043)	(0.071)
Difference	-0.064	-0.024	0.005	-0.043	0.023	0.035
	(0.079)	(0.062)	(0.066)	(0.060)	(0.062)	(0.090)
N	12243	12243	12243	12243	12242	12243
Panel B: Disaggreagted Effects, Girls						
Shock	0.193***	0.002	0.110**	-0.116**	0.019	0.101
	(0.067)	(0.033)	(0.055)	(0.055)	(0.033)	(0.076)
Insurance Uptake (Cum.)	-0.015	-0.011	-0.033	0.026	0.051	-0.078
	(0.075)	(0.064)	(0.065)	(0.054)	(0.066)	(0.089)
Shock × Insurance Uptake (Cum.)	-0.395**	-0.069	-0.233*	0.264*	-0.093	-0.314
	(0.177)	(0.095)	(0.140)	(0.146)	(0.095)	(0.207)
Shock+Uptake × Shock (coef.)	-0.202	-0.066	-0.122	0.148	-0.074	-0.213
Shock+Uptake × Shock (p-val.)	0.100	0.350	0.214	0.149	0.309	0.141
N	5421	5421	5421	5421	5421	5421
K-P F-stat	0.535	0.406	0.314	0.180	0.412	0.446
Panel C: Disaggreagted Effects, Boys						
Shock	0.006	0.026	-0.030	0.050	0.031	0.001
	(0.046)	(0.029)	(0.042)	(0.044)	(0.028)	(0.056)
Insurance Uptake (Cum.)	-0.054	-0.029	-0.139**	0.194***	-0.007	-0.301***
	(0.073)	(0.057)	(0.062)	(0.062)	(0.055)	(0.093)
Shock × Insurance Uptake (Cum.)	-0.005	0.018	0.121	-0.172	-0.017	0.230
	(0.121)	(0.087)	(0.108)	(0.108)	(0.084)	(0.152)
Shock+Uptake × Shock (coef.)	0.002	0.044	0.091	-0.122	0.014	0.231
Shock+Uptake × Shock (p-val.)	0.984	0.526	0.245	0.112	0.825	0.041
N	5857	5857	5857	5857	5856	5857
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

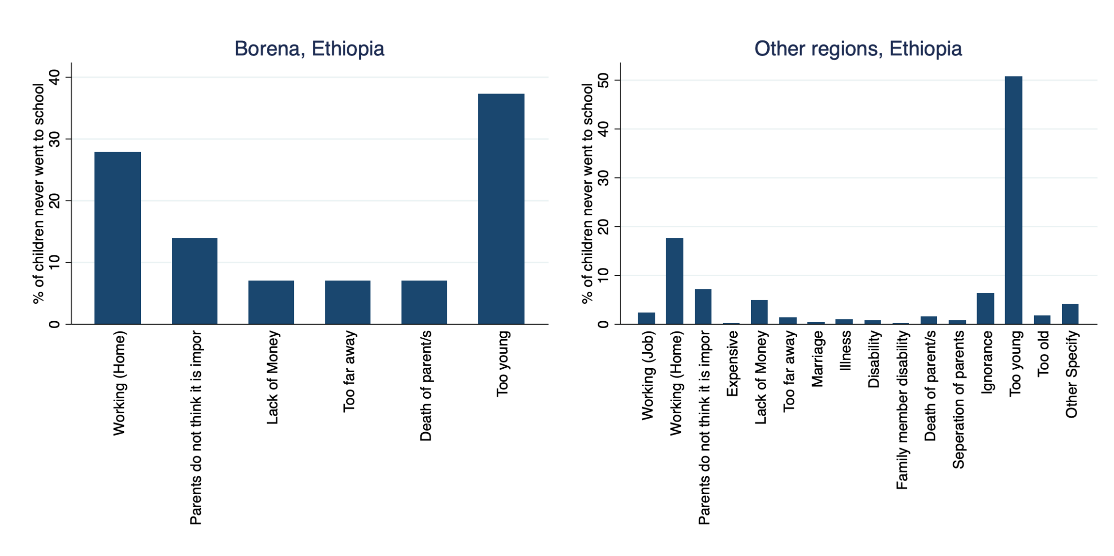
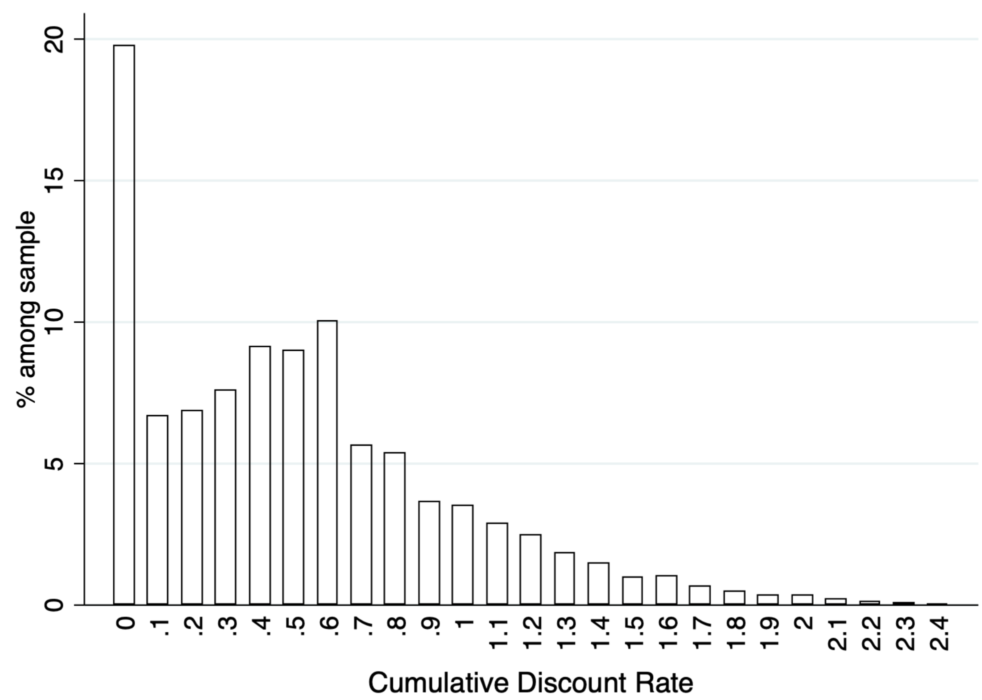


Figure A2: Cumulative discount rate and Insurance uptake

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



(b) Total number of Insurance uptake, the three recent sales seasons

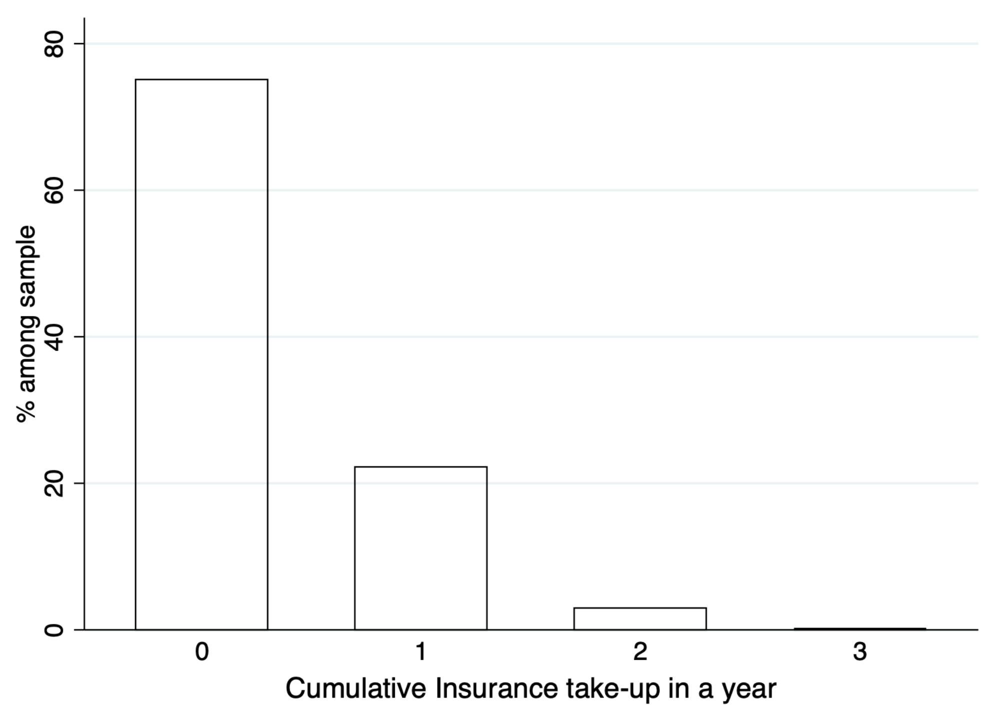


Table A1: First-stage predictive power of Table 3, Panel B

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 Child Activities (OLS)

	Child Labor	Work FT	Work and School	School FT	No activity
	(1)	(2)	(3)	(4)	(5)
Panel A: Average Effects					
Discount rate (Current + Cum.)	-0.034**	-0.010	-0.039***	0.047***	0.002
	(0.015)	(0.011)	(0.013)	(0.012)	(0.009)
N	12250	12250	12250	12250	12259
Mean of Dep. Var.	0.535	0.406	0.314	0.180	0.100
Panel B: Disaggregated Effects					
Shock	0.051*	0.006	0.015	-0.006	-0.015
	(0.026)	(0.015)	(0.024)	(0.024)	(0.012)
Discount rate (Current + Cum.)	-0.022	-0.008	-0.034***	0.041***	0.001
	(0.015)	(0.012)	(0.013)	(0.012)	(0.010)
Shock $\times$ Discount rate (Cum.)	-0.001**	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Shock+Uptake $\times$ Shock (coef.)	0.050	0.006	0.015	-0.005	-0.015
Shock+Uptake $\times$ Shock (p-val.)	0.055	0.676	0.534	0.819	0.217
N	12250	12250	12250	12250	12259
K-P F-stat	0.535	0.406	0.314	0.180	0.100

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 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 A4: 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 A5: 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 A6: 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 A7: 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 A8: 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.)	-0.134	-0.037	-0.181**	0.220***	-0.001
	(0.082)	(0.057)	(0.077)	(0.074)	(0.045)
Insurance Updatke (Lapsed)	-0.110	-0.027	-0.191	0.231	-0.013
	(0.148)	(0.093)	(0.140)	(0.141)	(0.078)
N	11319	11319	11319	11319	11326
K-P F-stat	29.105	29.105	29.105	29.105	29.129
AR test p-val.	0.098	0.723	0.015	0.000	0.966
Mean of Dep. Var.	0.535	0.406	0.314	0.180	0.100

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 IBLI Coverage in TLU

	Child Labor	Work FT	Work and School	School FT	No activity
	(1)	(2)	(3)	(4)	(5)
Insurance coverage (TLU)	-0.017*	-0.005	-0.019**	0.023***	0.001
	(0.009)	(0.006)	(0.008)	(0.008)	(0.005)
N	12219	12219	12219	12219	12226
F_{eff}	9.168	9.168	9.168	9.168	9.170
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.	0.034	0.432	0.007	0.000	0.877
Mean of Dep. Var.	0.427	0.374	0.272	0.161	0.193

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 (Country × Year FE)

	Child Labor	Work FT	Work and School	School FT	No activity
	(1)	(2)	(3)	(4)	(5)
Panel A: Average Effects					
Insurance Uptake (Cum.)	-0.092*	-0.013	-0.074	0.050	0.038
	(0.055)	(0.043)	(0.051)	(0.045)	(0.033)
N	12243	12243	12243	12243	12250
F_{eff}	30.083	30.083	30.083	30.083	30.086
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.	0.089	0.771	0.144	0.265	0.253
Mean of Dep. Var.	0.426	0.374	0.271	0.163	0.193
Panel B: Disaggregated Effects					
Shock	0.104**	0.025	0.059	-0.078*	-0.005
	(0.044)	(0.026)	(0.039)	(0.040)	(0.021)
Insurance Uptake (Cum.)	-0.001	0.009	-0.030	-0.015	0.038
	(0.073)	(0.061)	(0.067)	(0.058)	(0.048)
Shock × Insurance Uptake (Cum.)	-0.230**	-0.053	-0.110	0.164*	-0.002
	(0.113)	(0.076)	(0.100)	(0.098)	(0.062)
Shock+Uptake × Shock (coef.)	-0.126	-0.029	-0.051	0.086	-0.007
Shock+Uptake × Shock (p-val.)	0.110	0.611	0.465	0.196	0.885
N	11319	11319	11319	11319	11326
K-P F-stat	26.918	26.918	26.918	26.918	26.942
AR test p-val.	0.009	0.648	0.144	0.111	0.476
Mean of Dep. Var.	0.535	0.406	0.314	0.180	0.100

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 A11: 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.)	-0.084*	-0.028	-0.101***	0.117***	0.012
	(0.043)	(0.032)	(0.039)	(0.035)	(0.025)
N	10633	10633	10633	10633	10640
F_{eff}	48.790	48.790	48.790	48.790	48.796
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.	0.045	0.384	0.008	0.000	0.623
Mean of Dep. Var.	0.412	0.380	0.248	0.161	0.214

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 A12: 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.)	-0.078*	0.003	-0.105**	0.138***	-0.036
	(0.046)	(0.034)	(0.044)	(0.039)	(0.023)
N	8525	8525	8525	8525	8530
F_{eff}	49.567	49.567	49.567	49.567	49.553
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.	0.082	0.935	0.016	0.000	0.115
Mean of Dep. Var.	0.489	0.453	0.332	0.191	0.026

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.