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Does the Timing of Productivity Shocks in Childhood Affect Educational Attainment?*

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Abstract

Poor households in developing countries often face trade-offs between children's schooling and labor. Using data on pastoralist households in rural Kenya and Ethiopia–where livestock require care and generate within-household demand for child labor–I exploit quasi-random variation in rangeland grazing conditions that affects both household income and labor demand to estimate the impact of productivity shocks during childhood on educational attainment. Positive productivity shocks during preschool ages increase completed schooling, primarily by raising the probability of primary school entry, consistent with the relaxation of short-term liquidity constraints. In contrast, negative productivity shocks during primary school ages–when children are most likely to exit school and child labor productivity increases–are associated with higher educational attainment. This effect appears to operate through significant reductions in livestock holdings that lower subsequent demand for boys' labor in animal husbandry and probably reinforce the effect by inducing sedentarization. These results highlight the importance of non-separable household production and human capital decisions in shaping educational outcomes during critical stages of childhood in low-income settings.

JEL code: I25, O15, Q12

Keywords: human capital, child labor, opportunity cost, agricultural households, non-separability

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1 Introduction

Two hundred sixty-five million children, or 17% of the global child population, are engaged in labor, with even higher rates in Sub-Saharan Africa (Ortiz-Ospina, Esteban and Roser, Max, 2024). In low-income settings, households face trade-offs between schooling and child labor: while child labor provides immediate support, it comes at the cost of foregone returns to education. Existing work shows that labor market opportunities discourage schooling by raising its opportunity cost (Atkin, 2016; Shah and Steinberg, 2017). In much of the developing world, however, poor households engage primarily in smallholder agriculture with limited access to labor markets, where productive assets often require complementary child labor, generating within-household trade-offs with schooling (Allen IV, 2024; Ito and Shonchoy, 2026). As a result, shocks to agricultural production are theoretically ambiguous yet empirically important, as they simultaneously affect household income and within-household demand for child labor in ways that depend on the marginal productivity of child labor.

This paper introduces non-separable consumption, investment, and production decisions into the literature on human capital formation. I focus on agricultural households–specifically pastoralists in arid and semi-arid lands (ASALs) of Kenya and Ethiopia–whose livelihoods depend on extensive livestock grazing and in which child labor is commonly used as an input in livestock production. By combining household survey data with remotely sensed indicators of rangeland health as measures of shocks to livestock production (e.g., droughts), the paper tracks each child's exposure to these shocks from birth through early adulthood. This approach allows me to decompose the effects of productivity shocks by child age and gender, showing that income effects dominate at early ages, when child labor is uncommon, while at older ages the child labor channel becomes more salient–especially for boys, who bear a larger share of herding labor.

This setting provides an ideal context to study these mechanisms for three reasons. First, limited access to external labor markets and the widespread use of child labor in herding–particularly among older boys–allow for a clear examination of non-separable decisions between productive assets and human capital, generating variation in the opportunity cost of schooling in response to productivity shocks. Second, recurrent droughts over several decades, which are known to drive poverty traps through their effects on herd size (Lybbert et al., 2004; Santos and Barrett,

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2019), enable the estimation of age-specific effects of production shocks during childhood. Third, educational attainment is a particularly salient outcome in this context, as household heads in the baseline sample have completed less than one year of schooling on average.

This study combines two data sources: panel household surveys and the Normalized Difference Vegetation Index (NDVI). I use panel household survey data from pastoralist communities in the ASALs of northern Kenya and southern Ethiopia, which capture educational attainment, child time use, and detailed individual– and household–level characteristics, including household location, living standards, and herding practices. To measure shocks to livestock production, I use high-resolution satellite imagery available since 2000 to construct NDVI-based indicators of rangeland health, a well-established proxy for livestock productivity that correlates strongly with livestock mortality (Chantarat et al., 2013). I merge the two datasets using household geographic locations, constructing spatial buffers to define local rangeland conditions over the past 20 years. This approach allows me to measure each child's exposure to productivity shocks relative to the historical distribution throughout childhood.

I exploit spatial and temporal variation in productivity shocks affecting 3,748 children. I define asymmetric, censored NDVI z-scores relative to each community's historical distribution to identify positive and negative shocks to livestock production, and examine how exposure at different stages of childhood–from birth through the end of primary school age–affects completed years of education measured at endline (2020 in Kenya; 2022 in Ethiopia). The identification strategy relies on household and birth-year fixed effects, exploiting plausibly exogenous variation in the timing of shocks relative to a child's age. This approach enables sibling comparisons within households for the same shocks while netting out unobserved heterogeneity common to children born in the same year, such as macroeconomic shocks.

The results reveal an interesting decomposition pattern in the effects of productivity shocks to livestock production. Positive shocks during the preschool period significantly increase educational attainment: a cumulative one-standard-deviation positive shock during ages 3–5 raises completed years of education by 0.25 years (p-value 0.051), when children are typically too young to work. In contrast, negative shocks during mid-primary school ages–when dropout risk and demand for child labor are highest–have a significant *positive* effect on schooling. A one-standard-deviation negative shock during ages 9–11 increases completed years of education by 0.31 years (p-value 0.019). I find no evidence that negative shocks at any stage of childhood reduce educational attainment. Attrition is not differential with respect to shock exposure, and the results are robust to alternative specifications, including different treatments of missing shocks, spatial buffer sizes, and shock definitions.

To understand the mechanism, I first confirm that the negative productivity shock is associated with significant loss of livestock holdings. One-standard-deviation negative shock is associated with 3.4-3.8 Cattle Market Value Equivalent (CMVE) loss.[1]

I then examine the key trade-offs between the demand for child labor and income effects. Using panel data on child time use, I estimate the effects of current and lagged negative productivity shocks on subsequent child activities: herding, housework, and schooling. The results indicate that exposure to current and previous-year negative shocks reduces the probability of herding with the largest effects for older cohorts. In particular, older cohorts 12-14 got a persistent effects with the effect size of 6.0 percentage point decrease for a one-standard deviation negative shocks in the previous year (p-value = 0.001). In contrast, the probability of school attendance increases by 7.5 percentage points (p-value < 0.001) for the same cohort. These patterns appear to be reinforced by migration dynamics. While current droughts push herders to migrate farther, lagged shocks are associated with a significant reduction in subsequent migration (i.e., increased sedentarization), likely due to substantial livestock losses. This shift toward a more settled lifestyle may, in turn, have a positive effect on children's schooling.

Second, I examine heterogeneity by gender. Income effects are expected to be similar across genders, whereas girls are less likely to be affected by child labor demand in animal husbandry. During the preschool period, the estimated positive effects are not statistically different across genders, although the effect is statistically significant only for girls. This pattern is consistent with income effects dominating at ages when children are too young to work. In contrast, the effects of negative shocks during the mid-primary years are statistically significant only for boys (p-value = 0.017) and not for girls, although the gender difference itself is not statistically significant.

Finally, I turn to income effects. I first examine the direct impact of productivity shocks on income. Estimating income in this setting is challenging because wealth is largely held in the form of livestock, and income measures are noisy. Nonetheless, I find suggestive but imprecisely estimated positive effects of current and lagged positive shocks on milk income.

I further show that the positive effects of productivity shocks during the preschool years operate primarily through the extensive margin. Positive shocks–particularly at age five, just before school entry–increase the probability of completing any schooling by 5 percentage points ($p = 0.053$), with effects persisting into later educational attainment. This pattern is consistent with short-term liquidity constraints playing an important role in primary school enrollment, as many households appear to underinvest in education. These results are unlikely to be driven by early-life nutrition,

[1] In Kenya, 1 CMVE equals 0.625 camels, 1 cattle, or 10 goats/sheep; in Ethiopia, 1 CMVE equals 4 camels, 1 cattle, or 6.25 goats/sheep. See Barrett et al. (2025) for a detailed discussion.

as I find no significant effects during the first 1,000 days of life.

Overall, these findings highlight the central role of within-household demand for child labor, with trade-offs that vary systematically by child age and gender. At early ages, when children are largely too young to work, income effects dominate: positive productivity shocks relax short-term liquidity constraints at the point of primary school entry. As children grow older, the marginal productivity of child labor rises and the labor channel becomes more salient. In this stage, particularly for boys who bear a disproportionate share of physically demanding herding work, negative productivity shocks reduce livestock holdings and thus child labor demand, leading to higher schooling–an effect that may be further reinforced by reduced household migration.

This paper contributes to three strands of the literature. First, it adds to the literature examining how human capital formation is disrupted in contexts where child labor is prevalent. Existing studies show that improved labor market opportunities can discourage school participation by raising the opportunity cost of education (Ravallion and Wodon, 2000; Atkin, 2016; Shah and Steinberg, 2017; Ponnusamy, 2026). For example, Shah and Steinberg (2017) show that higher rural wages in India increase human capital investment in early life but reduce schooling during school age, when the opportunity cost of education rises due to improved labor market opportunities.[2] Edmonds and Theoharides (2020) shows that asset transfers can unintentionally increase adolescent labor at the extensive margin in the Philippines.

This paper complements this literature by focusing on within-household child labor demand in non-separable agricultural households–conditions common among poor households in developing countries. In the context of child labor in agricultural households, related work focused on the trade-offs of child time use in farming and schooling. Allen IV (2024) leverages a shift to the school calendar in Malawi and shows that increase in school calendar overlap during peak farming periods significantly decrease schooling (and share of children engaged in peak-period after four years). Ito and Shonchoy (2026) leverages the timing of Ramadan school holidays, they find that annual exams coinciding with the harvest season increase school dropout significantly among agricultural households in Bangladesh. This paper highlights how negative productivity shocks reduce the demand for child labor by destroying productive assets, thereby lowering child labor heterogeneously and increasing educational attainment with implications on educational attainment.

Second, this study contributes to the literature on the long-run effects of economic and climate

[2] Atkin (2016) show that expansions in export-oriented manufacturing in Mexico raise school dropout rates by increasing low-skill labor demand; Ponnusamy (2026) find that positive rainfall shocks during early adolescence in Pakistan lower test scores by increasing school absenteeism and child labor; and Zimmermann (2020) document that in rural India positive rainfall shocks increasingly reduce school enrollment–especially among older children and girls–through higher opportunity costs of schooling.

shocks experienced during early childhood and school age on later outcomes (Alderman, Hoddinott, and Kinsey, 2006; Maccini and Yang, 2009; Shah and Steinberg, 2017; Carrillo, 2020; Pelli and Tschopp, 2025).[3] I introduce a framework of non-separable agricultural households, in which child labor is an input into household production and its marginal productivity varies by age and gender. Consistent with prior evidence, positive shocks during early childhood improve educational outcomes when child labor demand is limited (Maccini and Yang, 2009; Alderman, Hoddinott, and Kinsey, 2006). I show, however, that these effects operate primarily by relaxing liquidity constraints at the time of school entry, rather than through early-life nutrition or child health. In contrast to much of the existing literature,[4] I find that negative productivity shocks during mid-primary school ages may increase educational attainment by reducing household productive assets and, lowering demand for child labor, particularly among older boys. These findings provide new insight into how opportunity costs and schooling decisions evolve in settings where child labor is closely tied to household production and access to outside labor markets is limited.

Third, this paper contributes to the policy discussion on the risks that climate change poses to agricultural-dependent households. In arid and semi-arid lands (ASALs), recurrent droughts and catastrophic herd losses can generate poverty traps (Lybbert et al., 2004; Barrett, Carter, and Little, 2006; Santos and Barrett, 2011; Barrett et al., 2019). For example, Toth (2015) documents a bifurcation in pastoralist strategies, whereby households with larger herds–measured in tropical livestock units (TLU)[5]–pursue high-return migratory strategies, while smaller-asset households remain trapped. Recent work shows that drought insurance can mitigate the adverse effects of shocks (Jensen, Barrett, and Mude, 2017; Janzen and Carter, 2019) and, in particular, support human capital formation by reducing child labor demand (Barrett et al., 2025; Son, 2025). This paper complements these findings by showing that weather shocks affect human capital formation heterogeneously, depending on the marginal productivity of child labor. The results imply that financial interventions at the preschool stage–when liquidity constraints are most binding–can improve educational outcomes, while cautioning that asset-based interventions, such as livestock transfers, may unintentionally increase child labor demand. They also underscore the importance of financial instruments, such as insurance, to protect households against severe drought-related losses.

The remainder of the paper is organized as follows. Section 2 describes the study setting and data. Section 3 presents the conceptual framework. Section 4 outlines the empirical strategy,

[3] See Venegas Marin, Schwarz, and Sabarwal (2024) and Prentice et al. (2024) for recent reviews.

[4] For example, Huang and Dong (2025) show that flood exposure reduces schooling through income losses and higher opportunity costs.

[5] TLU is a standardized unit that aggregates different livestock types based on live weight and nutrient requirements: 1 TLU = 1 cattle = 0.7 camel = 10 sheep/goats.

identification assumptions, and main results. Section 5 examines the underlying mechanisms. Section 6 concludes with policy implications.

2 Data and background

2.1 Household survey of pastoralists: education and child labor

Pastoralism is the primary livelihood strategy for residents of the arid and semi-arid lands (ASALs) of northern Kenya and southern Ethiopia, enabling households to generate income in otherwise infertile drylands. Livestock serve as both productive assets and primary stores of wealth, but they are highly vulnerable to climate shocks, disease, and predation. Given the central role of milk production in household income, investment in livestock inputs—particularly veterinary services—can be a high-return strategy by reducing mortality and sustaining lactation rates (Sieff, 1999; Admassu et al., 2005; Homewood et al., 2006). Nevertheless, the uptake of veterinary services remains low among pastoralists. Herd size and mobility are also critical for long-term well-being, as mobility enables access to dispersed grazing resources. However, mobility is labor-intensive, making it costly for households with small herds or limited labor supply and thereby restricting their ability to fully utilize communal rangelands (Toth, 2015).[6]

I use individual- and household-level data from panel surveys conducted by the International Livestock Research Institute (ILRI). In Kenya's Marsabit County, the baseline survey was conducted in 2009, followed by annual surveys through 2015 (except 2014) and an endline survey in 2020. In Ethiopia's Borena Zone, the baseline survey took place in 2012, followed by annual surveys through 2015 and an endline in 2022. Additional details are available through ILRI's data portals.[7] Households were randomly selected within pre-baseline herd-size strata across 16 locations in Marsabit and 17 in Borena, chosen to capture variation in environmental conditions and remoteness. Sample sizes were allocated proportionally across strata, yielding 924 households in Kenya and 515 in Ethiopia (see Appendix Figure A1 for the study locations).

The surveys collected comprehensive information on households' living standards, herding practices, and child time use and educational attainment. Appendix Table A1 presents household-level summary statistics on livestock holdings and losses in the baseline. I use Cattle market-value

[6]Seasonal migration plays a crucial role in sustaining herd size by allowing pastoralists to access spatially and temporally varying forage and water resources (Chantarat et al., 2017).

[7]The IBLI dataset is publicly available at `https://hdl.handle.net/20.500.11766.1/FK2/S19DC6`. The codebook is available at `https://data.ilri.org/portal/dataset/ibli-marsabit-r1` (Kenya) and `https://data.ilri.org/portal/dataset/ibli-borena-r1` (Ethiopia).

equivalent (CMVE) to standardize a unit used to aggregate animals across different types based on their market values, utilizing panel survey data. The average herd size is 22.64 CMVE, though the distribution is right-skewed (median = 11.08 CMVE). Notably, the average livestock loss over the past 12 months is 10.48 CMVE, accounting for nearly half of the total herd size.

I focus on a sample of pastoralist children born between 2000 and 2014 in Kenya and between 2005 and 2015 in Ethiopia. These cohorts are the ones whose educational attainment and shock experiences during childhood are well defined.[8]

Table 1 presents summary statistics for the child-level outcome variables used in the analysis by gender, for individuals aged 6-20 in Kenya and 7-17 in Ethiopia at endline survey. The main outcome variable is the completed years of education (note that some of them may not have completed education yet) where the mean is 3.29.[9] Given I compare the children within the same cohorts (i.e., a cohort fixed effects model in the regression analysis), this outcome should capture any deviation from expected education progression such as dropping out, coming back to school, and retention. Primary education is compulsory and free in both countries, but households often incur out-of-pocket expenses for transportation, uniforms, school supplies (such as textbooks), exam fees and school food.[10] The average probability of being in age-appropriate education is only 25%, while currently attending any school is 56%.[11] A considerable share of children are engaged in work: even when restricting the definition to livestock and housework, 69% of them participate in these activities. Meanwhile, 56% of the sample children still attend school, which suggest balancing work and school is relatively common particularly for housework (Son, 2025).

Appendix Table A2 reports the variables used in the analysis. The average age of children in the sample is 12.2 years, and 55% are male. 33% are firstborn, followed by 28% secondborn, 19% thirdborn, and 20% fourth-born or higher. Importantly, 95% of sampled children have at least one

[8]The starting year is chosen because NDVI data are only available from 2000 onwards. The upper limit is determined by school entry age—6 in Kenya and 7 in Ethiopia–so outcomes are only relevant for those who should have been primary school before the last survey round, i.e., those born in 2013 or earlier in Kenya and 2014 or earlier in Ethiopia. Additionally, the endline Ethiopian data includes information only for cohorts aged 5–17.

[9]The Kenyan educational system consists of eight years of compulsory and free primary education, followed by four years of secondary education, and an additional four years of university education for those pursuing higher studies. The Ethiopian system follows an eight-year primary education structure, followed by two years of general secondary education, and two additional years of preparatory secondary education for students intending to pursue higher education, which typically lasts three to four years at the university level. The official entry age for primary school is six in Kenya and seven in Ethiopia. The school calendar typically begins in January in Kenya and September in Ethiopia.

[10]In the baseline survey, households spent an average of $42 USD annually on out-of-pocket education expenses, accounting for nearly 10% of their cash income.

[11]Age-appropriate education is defined as years of education by comparing a child's age, the years of education at endline, and the legal age of education in each country. In Kenya, the legal age to start education is six, seven in Ethiopia. Therefore, if a eight-year old completed one year of education then she has completed the age-appropriate years of education in Ethiopia but if she lived in Kenya we would not classify her similarly.

Table 1: Summary statistics of education and child labor by gender

	(1) Full sample Mean/SD	(2) Female Mean/SD	(3) Male Mean/SD	(4) Pairwise t-test Mean/SD
Years of education	3.29	3.59	3.04	0.56***
	[3.64]	[3.56]	[3.70]	
Age appropriate education (=1)	0.25	0.28	0.22	0.06***
	[0.43]	[0.45]	[0.41]	
Educational attainment gap (yrs.)	2.15	1.60	2.60	-1.00***
	[3.81]	[3.08]	[4.28]	
Schooling (=1)	0.56	0.62	0.52	0.09**
	[0.50]	[0.49]	[0.50]	
Herding labor (=1)	0.43	0.22	0.59	-0.37***
	[0.50]	[0.41]	[0.49]	
Housework (=1)	0.26	0.49	0.09	0.40***
	[0.44]	[0.50]	[0.28]	
Observations	3748	1699	2049	3748

Notes: Column 1 shows mean and standard deviations (square bracket) for full sample, while columns 2 and 3 divided into female and male, respectively. Column 4 gives a difference in means and statistical difference of pairwise t-test. The sample is restricted to individuals aged 6-20 in Kenya and 7-17 in Ethiopia years as of the 2020 in Kenya (R7 survey) and 2022 in Ethiopia (R5 survey). "Years of education" is measured for everyone at endline survey including those who are still at school, not necessarily those who have completed education. "Age-appropriate education" is a dummy which is defined as years of education by comparing her age, the years of education at endline, and the legal age of education in each country. "Educational attainment gap" is defined as years of education which is supposed to be in age-appropriate education, compared to the actual current years of education. "Schooling", "Working for livestock," and "Working for housework," are defined based on children's activities, depending on whether their reported activities include any schooling, any work related to livestock, or any work related to housework as either a primary or secondary activity. The data on child time use is available only for Ethiopia ($N = 948$). * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

sibling, with an average of 3.76 siblings including themselves, which supports the use of household fixed effects in the regression analysis below.

Figure 1 illustrates gender differences in patterns of child labor. First, children of both genders typically begin working between ages 7 and 10, with almost no labor participation before these ages.[12] Second, there are pronounced gender differences in the type of work performed: a much larger share of boys engage in livestock-related activities, whereas a greater proportion of girls perform housework, with the difference statistically significant at the 1% level. This pattern likely reflects the nature of herding, which is physically demanding and often requires working away from home, including through seasonal migration, making it difficult to perform on a part-time basis. Livestock-related activities include herding animals, cleaning and caring for them, feeding animals at the main base camp, milking lactating animals, and selling livestock products (FAO,

[12]During fieldwork, a local chief noted that children are typically introduced to livestock at ages 7–8.

Figure 1: Share of children engaged in herding and housework by age and gender

Notes: "Herding labor" and "Housework" are dummy variables indicating whether a child's primary or secondary activity includes either task. The sample is restricted to individuals aged 17 or younger in Ethiopia at the time of the endline survey. Data on child time use is not available for Kenya or for individuals older than 17 in Ethiopia. The points represent averages for each age, with red for females and blue for males.

2013).[13] In contrast, housework—more commonly performed by girls–can be more easily combined with schooling.

Females significantly outperform males in education outcomes in this context. Completed years of education are, on average, 0.53 years higher for females, despite males in the sample being 0.61 years older on average.[14][15] Appendix Figure A2 illustrates average completed years of education by age at the endline survey and child gender. Educational attainment increases with age, with notable cohort-specific variation and substantial heterogeneity across gender. Across most ages, females have more completed years of education on average, and the gender gap appears to widen around grade 3 (corresponding to age 7 in Kenya and age 8 in Ethiopia), which coincides with the age at which boys typically begin participating in livestock-related work. Appendix Figure A3

[13]Male children are more likely to take on herding responsibilities once they reach a certain age (Kenea, 2019), typically for smaller ruminants (e.g., goats and sheep) rather than larger animals such as cattle or camels, which are generally managed by adult men.

[14]Firstborn children are more likely to be male, while children born fourth or later are less likely to be male.

[15]These patterns may also reflect other factors, such as higher average returns to education for females (Psacharopoulos, 1994) or higher exit rates of daughters from households due to their value in securing bride price (Villa, Barrett, and Just, 2011).

presents completed years of education by baseline herd size measured in tropical livestock units (TLU). Consistent with higher within-household demand for child labor, children from households with larger livestock holdings exhibit lower educational attainment on average.[16] Taken together, these patterns suggest that within-household demand for child labor in livestock production plays an important role in shaping educational attainment.

2.2 NDVI data: productivity shocks

Droughts has been severely impacted pastoralists' livelihoods by disrupting livestock herding and productivity, their primary asset and income source. Low-input pastoralism is vulnerable to catastrophic drought shocks; drought-related starvation and dehydration account for 47 percent of the livestock losses in the region (Jensen, Barrett, and Mude, 2016). While livestock markets could theoretically buffer these shocks by enabling sales in adverse seasons and purchases in favorable ones, the widespread nature of droughts leads to simultaneous sales, causing price collapses that coincide with reduced animal productivity and survival, exacerbating wealth risks (Barrett et al., 2003). Limited access to financial services, such as credit and insurance, forces pastoralists to rely on herd accumulation as their main risk management and recovery strategy, with larger pre-drought herds correlating with better post-drought herd survival (Lybbert et al., 2004; McPeak, 2005; Barrett and Swallow, 2006; Cissé and Barrett, 2018). In response, they adopt coping strategies like mobility, opportunistic herd management, and veterinary investments, though access to such services is uneven (Admassu et al., 2005; Homewood et al., 2006; Sieff, 1999; Santos and Barrett, 2011; McPeak, Little, and Doss, 2012). However, distress sales during droughts flood markets, further depressing livestock prices and depleting pastoralists' primary productive asset, complicating recovery (Barrett et al., 2003). Liquidating livestock to buffer consumption during shocks also reduces expected future income, deepening long-term vulnerability (McPeak, 2004).

I use high-resolution satellite data from USGS to track the life history of exposure to droughts for each household since 2000.[17] The NDVI data indicate photosynthetic activity in observed vegetation, as reflected in spectral data remotely sensed from satellite platforms at high spatiotemporal resolution.

NDVI is a suitable measure to capture the productivity shocks of livestock production for at least two reasons in this setting. First, NDVI has shown a high correlation with livestock mortality

[16] This pattern aligns with the "wealth paradox," whereby greater household assets increase the demand for child labor and induce children to leave school (Bhalotra and Heady, 2003).

[17] More specifically, I use MOD13Q1.061 Terra Vegetation Indices 16-Day Global 250m. See `https://doi.org/10.5067/MODIS/MOD13Q1.061` for the details.

(Chantarat et al., 2013), ensuring it accurately captures the relevant shocks to pastoralist households. Second, this measure reflects the combined effects of rainfall history, competition from wildlife, and hydrology. It thus captures the idea that a series of low rainfall events has a more detrimental impact than a single, isolated drought.[18,19]

I define exposure to productivity shocks using asymmetric, censored NDVI z-scores, calculated relative to the historical distribution within each community at the household level. This measure captures deviations in vegetation health and productivity that reflect local environmental conditions affecting household livestock production. The buffer sizes and cutoff values used to define productivity shocks are chosen using a data-driven approach that maximizes predictive power for livestock mortality. Specifically, I define shocks as deviations of 0.5 standard deviations from the historical distribution, using a 5 km buffer for positive shocks—when pastoralists typically do not need to migrate farther—and a 15 km buffer for negative shocks, which better captures conditions associated with seasonal migration to satellite camps during drier periods.[20]

More specifically, for household h in community j for year y, I define negative and positive productivity shock as follows:

$$\theta^{-}_{hjy} := |NDVI^{-}_{hjy}| * NDVInorm_{hjy} \text{ if } NDVI_{hjy} \leq 0 \tag{1}$$

$$\theta^{+}_{hjy} := NDVI^{+}_{hjy} * NDVInorm_{hjy} \text{ if } NDVI_{hjy} \geq 0 \tag{2}$$

where $NDVI^{-}_{hjy}$ and $NDVI^{+}_{hjy}$ are the truncated z-score of the NDVI relative to community j for those have negative and positive values, respectively. The term $NDVInorm_{hjy}$ is an indicator variable that takes the value 0 for NDVI z-scores within the range $[-0.5, 0.5]$, reflecting typical or non-shock conditions, and 1 otherwise. Essentially, this formulation captures the magnitude of deviation from average conditions, quantifying significant deviations that exceed or drop below one standard deviation, while assuming no impacts within the $[-0.5, 0.5]$ standard deviation interval.

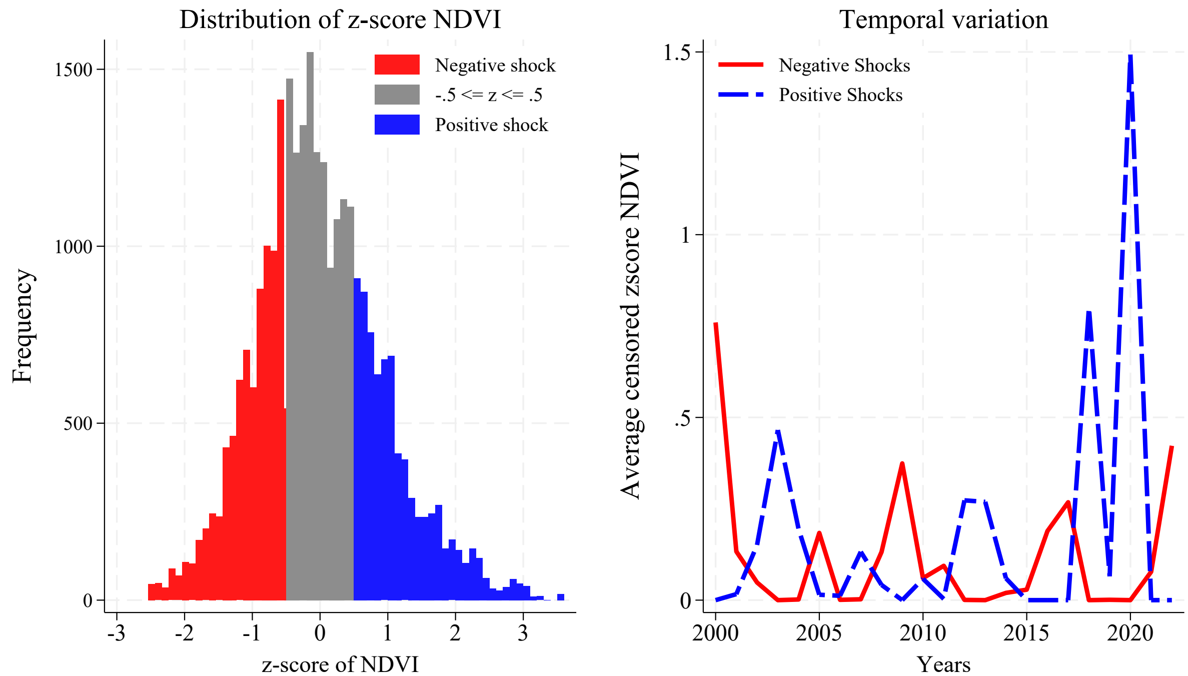
Figure 2 illustrates the definition and temporal variation of productivity shocks. The left panel displays the histogram of NDVI z-scores, which is approximately normally distributed, with the highest density concentrated in the interval $[-0.5, 0.5]$ and relatively long tails on both the positive and negative sides. Red bars correspond to negative shocks and blue bars to positive shocks, which are assigned as continuous measures of shock intensity.

[18]Note that there may be occasional river-prone flooding, but its effects on herding should operate through vegetation, which is captured by NDVI. This ensures that the variation is accounted for and the interpretation remains unchanged.

[19]Appendix figure A4 and A5 show the distribution of NDVI and its z-score during the study periods.

[20]Appendix Figure A6 shows a strong positive correlation between NDVI buffered at 5 km and 20 km.

Figure 2: Definition and temporal variations of productivity shocks



Notes: The left panel shows a histogram of NDVI z-scores buffered within a 15 km radius around each household location. Red bars indicate negative shocks (values below -0.5), black bars represent normal years (values between -0.5 and 0.5), and blue bars indicate positive shocks (values above 0.5). The right panel plots the average censored NDVI z-score in the sample since 2000. The red line represents negative shocks, while the blue dotted line represents positive shocks.

The right panel illustrates temporal variation in productivity shocks over the study period.[21] The y-axis reports the average censored NDVI z-score, constructed as a weighted measure that captures both the incidence and severity of shocks. The figure shows that productivity shocks are recurrent, with pronounced negative spikes in the early 2000s, 2009, 2016–17, and 2022. In contrast, positive shocks generally exhibit opposing dynamics over time.[22]

This definition has several advantages relative to alternative measures. First, it allows more severe shocks to have larger impacts, effectively distinguishing extreme shocks from moderate fluctuations. Second, it accommodates asymmetry between negative and positive shocks, which are likely to differ in magnitude and mechanisms in this setting. Third, the measure is likely ro-

[21] See Appendix Figure A7 for country-specific patterns.

[22] Appendix Figure A8 illustrates spatial variation in NDVI during the 2009 drought in Marsabit, Kenya. Despite accounting for spatial buffering, substantial heterogeneity remains, with some areas exhibiting NDVI values close to zero and others showing greener conditions with values up to approximately 0.6. The empirical analysis below primarily exploits temporal variation in shocks within households, using household fixed effects.

bust to endogenous livestock choices, as shocks are defined relative to the community's historical distribution of NDVI rather than household-level outcomes.[23] See Appendix Section B for further discussion. For NDVI values, I compute the average annual NDVI within the buffer around each household's location.[24] This approach accounts for heterogeneity in trekking strategies and seasonal movements. Liao et al. (2017) study migration patterns among Ethiopian pastoralists using GPS collars that tracked cattle movements every five minutes over a 200-day period. They find that most pastoralists operate from a base camp close to their homes, with mean migration distances of approximately 5–10 km. Some households migrate seasonally to satellite camps, particularly during drier conditions, but these movements generally remain within a 20–25 km radius of the base camp. Only a small share of households travel beyond this range when necessary.[25]

NDVI is likely to be correlated across years, which is beneficial for capturing cumulative effects. However, this correlation can make it challenging to estimate the impact of shocks occurring at different times separately with precision. In my sample, the empirical correlation between shock variables is 0.17 (95% confidence interval: [0.157, 0.185]) for negative shocks and 0.089 (95% CI: [0.071, 0.108]) for positive shocks. Appendix Figures A9 and A10 display the full correlation matrix. I address the robustness of the findings in Section 4.

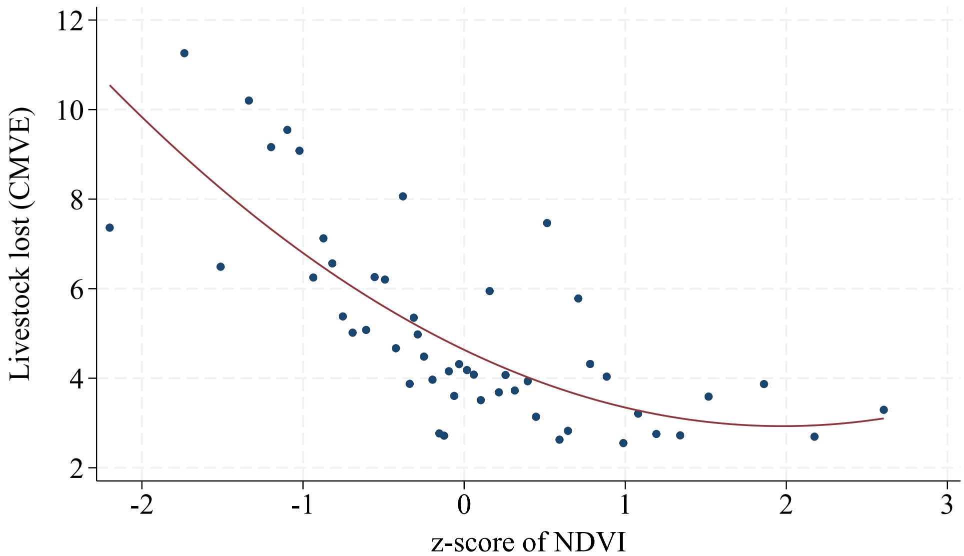
Figure 3 shows the relevance of the constructed productivity shock variables by examining the relationship between the NDVI z-score and reported livestock loss using panel household surveys. The figure illustrates a clear negative relationship between the z-score NDVI and reported livestock lost in the past 12 months with particular jump around -.5. Appendix Table A3 examines the relationship between livestock loss outcomes and productivity shocks, both with and without household fixed effects. Negative shocks are associated with reported losses of approximately 3.4 to 3.8 CMVE. This is economically significant, as it is approximately equivalent to 21–23 goats or sheep, 2.1–2.3 camels, or 3.4–3.8 cattle loss. Conversely, positive shocks result in the opposite effect as expected: compared to normal periods, livestock losses decrease by approximately 0.8 to 1.1 CMVE. In terms of the actual numbers, Appendix Figure A11 illustrates the relationship between the annual change in livestock holdings (CMVE) and lagged NDVI z-scores, showing a positive correlation with a large magnitude. The pattern is very similar if I restrict the reason to droughts.

[23] For outliers who experience more than five shocks over the study period, I focus on the five most extreme positive or negative shocks and treat other periods as non-shocks.

[24] Although grazing patterns are seasonal, there is no specific period during which grazing does not meaningfully affect livestock production. I therefore use the annual average.

[25] Location data are typically collected in the baseline and endline surveys. Because the analysis relies on the endline sample, I assume that household locations remain fixed over the survey period. For the pre-survey period, I impute locations based on survey information. Although some households may have changed location, this is unlikely to materially affect the results given the buffered approach and the inherently mobile nature of pastoral households.

Figure 3: Relationship between z-score NDVI and livestock lost



Notes: The figure shows the binned-scatter relationship between the NDVI z-score, computed within a 15 km buffer around each household location, and reported livestock losses from any cause measured in CMVE over the past 12 months, using 30 quantile bins. The data come from a household panel survey conducted in Kenya in 2009, 2010, 2011, 2012, 2013, 2015, and 2020, and in Ethiopia in 2012, 2013, 2014, 2015, and 2022. In Kenya, 1 CMVE equals 0.625 camels, 1 cattle, or 10 goats/sheep, while in Ethiopia, 1 CMVE equals 4 camels, 1 cattle, or 6.25 goats/sheep.

3 Conceptual framework

Consider, from a theoretical perspective, how exposure to productivity shocks may affect child schooling in a context where child labor is closely linked to productive assets. I follow the theoretical foundations in the existing literature and derive testable implications for this setting (Basu and Van, 1998; Colmer, 2021).

This analysis is characterized by three key features that depart from the standard setting. First, access to outside labor markets is limited.[26] Second, child labor—particularly among boys—plays a significant role in managing productive assets within households.[27] Third, access to financial markets is largely absent.

Livestock production requires labor inputs from both adults and children, with adult labor assumed to be supplied inelastically for simplicity.[28] Children allocate their time between agricul-

[26]In the baseline sample, only about 10% of the working-age population engages in casual labor (e.g., herding for pay) or wage or salaried employment as a primary or secondary activity.

[27]64% of children in the sample contribute to work.

[28]In the baseline roster, 57% of the working-age population engages in livestock-related activities as a primary or secondary economic activity. Among these individuals, the median number of hours worked is 8.

tural work and schooling (Allen IV, 2024; Ito and Shonchoy, 2026). Given the near absence of external labor market opportunities for children, their labor is supplied almost exclusively within the household.[29]

Households derive utility from both consumption and their children's human capital.[30] However, in the presence of incomplete credit and labor markets, household production and consumption decisions are nonseparable. As a result, children's labor contributes to household utility by increasing current income–and thus consumption–while simultaneously reducing education.

Households face both the opportunity cost of schooling, arising from child labor opportunities, and the direct financial cost of education. Consider exogenous weather shocks, such as droughts, that affect livestock production. A drought shock can influence schooling through two opposing channels. First, through an income effect, droughts reduce livestock productivity and herd size, lowering household income and increasing the marginal utility of consumption. This raises the opportunity cost of investing in education and may push children into work. Second, droughts may reduce herd size and thus lower the demand for child labor.[31] As a result, the net effect of productivity shocks on human capital investment is theoretically ambiguous.

The effects are likely heterogeneous across child characteristics, such as age and gender, which determine the financial and opportunity costs of schooling (Figure 4). The financial cost of schooling increases sharply at the age of school entry and then remains relatively constant thereafter, common across gender. Under the assumption of imperfect or absent financial markets, productivity shocks affect educational decisions through the income channel: when a household's budget constraint is binding, positive productivity shocks relax resource constraints, while negative shocks tighten them. At very young ages, children are typically too young to work, so child labor demand is not yet operative.

Next, I turn to heterogeneity in opportunity costs. Boys have a higher marginal product of labor than girls in animal husbandry as discussed in the previous sections.[32] This implies that, on average, girls attain higher levels of educational attainment than boys. This prediction is also con-

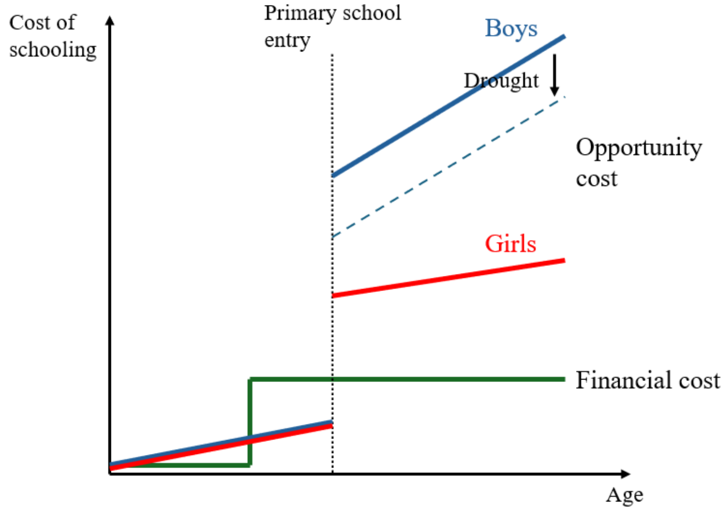
[29] 43% of the sample report contributing to livestock-related work (including household-owned herding, livestock production such as milk, or livestock trading), while none report engaging in casual labor (e.g., herding for pay) or wage or salaried employment as a primary or secondary activity.

[30] This can be interpreted as higher future income, with schooling serving as an investment in future periods.

[31] Conversely, positive productivity shocks may increase livestock productivity and household income through an income effect. Whether such shocks also increase demand for child labor is an empirical question, as favorable conditions may raise income through milk production without necessarily expanding herd size.

[32] Specifically, the labor value of caring for camels and cattle increases as boys grow larger and stronger, particularly around ages 10–12, while it remains negligible at younger ages because camels are large and powerful animals. For goats, the marginal product of labor begins to rise at younger ages, around 7 or 8, as goats are smaller and more manageable. The marginal product of labor for cattle lies between that of camels and goats, as cattle are smaller and more docile than camels.

Figure 4: Financial and opportunity costs of schooling by age and gender under drought



Notes: This figure provides a conceptual summary of the financial and opportunity costs associated with schooling across childhood. Financial costs are depicted by the green line, while opportunity costs vary by gender—shown in blue for boys and red for girls. Opportunity costs increase with age as the marginal productivity of child labor rises, particularly for boys in livestock herding. Droughts affect schooling decisions by reducing the demand for boys' labor, illustrated by the downward shift in the opportunity cost after the drought (dotted line).

sistent with alternative mechanisms documented in the literature, such as higher average returns to education for females (Psacharopoulos, 1994) or gendered household preferences in human capital investment. In this setting, Villa, Barrett, and Just (2011) suggest that households may allocate more nutritional resources to unmarried girls due to expected returns in the marriage market.[33]

Although this section focuses on pastoralist households, the findings are likely to extend to other developing-country settings characterized by thin labor markets. A key feature of the analysis is that demand for child labor is complementary to productive asset holdings: exogenous shocks to these assets affect household income and labor demand in opposing directions, yielding theoretically ambiguous predictions for schooling. This framework complements studies examining how increased outside labor market opportunities raise the opportunity cost of schooling, such as Shah and Steinberg (2017) and Atkin (2016). More broadly, the discussion underscores the importance of accounting for within-household labor demand when analyzing human capital investment.

I test these predictions in Section 4.

[33]Even if the direct financial cost of schooling exceeds the opportunity cost of child labor, the qualitative implications remain unchanged.

4 Identification Strategy and Results

4.1 Baseline specification

I use a history of NDVI deviations to assess the impact of productivity shocks during childhood on educational attainment. I estimate the following regression equations: for an individual i household h residing in location j born in year t

$$S_{ihjt} = \sum_b (\zeta_b^{-,k}\theta_{h,b}^{-,k} + \zeta_b^{+,k}\theta_{h,b}^{+,k}) + \lambda_h + \phi_t + \mathbf{X}'_{ih}\beta + \varepsilon_{ihjt}^k \quad \text{for } k = \{max, cumulative\} \tag{3}$$

In this equation, S_{ijht} represents the completed years of education at the endline survey for an individual i in household h residing in community j for birth year t. The outcome variable is completed years of education measured at the endline survey. $\theta_{h,b}^{-,max}$, $\theta_{h,b}^{+,max}$, $\theta_{h,b}^{-,cum}$, and $\theta_{h,b}^{+,cum}$ are the maximum or cumulative censored z-score NDVI in absolute value to capture the different effects of negative and positive productivity shocks of age bins of infants age (0-2), preschoolers age (3-5), early primary age (6-8), mid primary age (9-11), and late primary age (12-14).[34,35] λ_h represents a vector of household fixed effects, while ϕ_t is a vector of birth-year fixed effects. $\mathbf{X}_{ih}$ is a vector of individual- and household-level controls that includes indicators for the child's gender and birth order, the number of school-aged children in the household, and livestock wealth in CMVE. $\zeta_b^{-,k}$ and $\zeta_b^{+,k}$ represent the coefficients of interest, capturing the average effects of negative and positive shocks on livestock production – measured as one standard deviation from normal years of rangeland health conditions – at a given age bin. When shocks are defined cumulatively, they capture the accumulated effects of shocks experienced within a given age bin. Alternatively, when defined as the best or worst shock, the measure captures the most severe positive or negative shock occurring within that period. Standard errors are clustered at the village level, as shocks are likely to be correlated within villages.

With the inclusion of household fixed effects, this approach compares siblings and identifies the average effects of shocks experienced at different ages. This strategy excludes only children without siblings; however, 95% of children in the sample have at least one sibling. By doing so,

[34] Appendix Figure A13 presents the shock experiences by year, while Appendix Table A4 shows the variation in binned ages at the time of shocks, which are used in the regression analysis for worst/best and cumulative productivity shocks.

[35] For children who have not yet reached the age of experiencing shocks—for example, a 7-year-old child who does not experience shocks at age 10–I impute this value as zero. It is important to note that, with the inclusion of birth year fixed effects, this imputation follows the approach outlined by Zhao and Ding (2024), which addresses missing data using a missing indicator method.

the analysis attributes variation in outcomes to the timing of shock exposure within households, comparing siblings exposed to the same shock at different stages of childhood. A potential concern is that this comparison may be restrictive. As a robustness check, I also implement a less restrictive specification with community fixed effects, which control for cohort-invariant unobserved factors common to individuals within the same village; the results remain robust.

With the inclusion of birth-year fixed effects, I control for unobserved heterogeneity common to all children in the sample born in the same year, such as macroeconomic shocks. The identification strategy relies on the assumption that variation in exposure to productivity shocks is exogenous, conditional on these fixed effects and the included control variables.

4.2 Threats to identification

There is a concern regarding attrition in the endline survey. Specifically, individuals who remain in the sample may differ systematically from those who attrit, potentially biasing the estimates. I discuss these issues in detail in Appendix C.

At the household level, the research team successfully tracked 82 percent of baseline households (1,179 out of 1,439). At the child level, 22.8% of children attrited by the endline survey. Attrition was more likely among households that were female-headed, had fewer adults, or did not own agricultural land (Barrett et al., 2025). At the child level, older children and girls were more likely to attrit relative to the baseline survey conducted approximately ten years earlier, possibly reflecting girls exiting the sample due to marriage (Appendix Tables C1 and C2).

There are two potential threats to identification. First, endogenous household migration decisions in response to productivity shocks could confound the causal effect of shocks on educational attainment. I find no evidence of differential attrition based on the cumulative number of productivity shocks over the past 20 years (Appendix Table C3), which mitigates concerns that endogenous migration biases the estimates. Moreover, the identification strategy relies on sibling comparisons, so bias does not arise simply because migrating households are wealthier or more educated. Instead, bias would occur only if attrition is correlated with unobserved, within-household preferences–such as a systematic tendency to invest differentially in firstborn sons among migrating households.

Second, endogenous fertility responses or selective mortality may also generate sample-selection concerns. For example, if droughts disproportionately affect weaker or younger children, the estimates may be biased downward, as household fixed effects comparisons would then be made among relatively stronger siblings. Fertility responses could also matter if households experiencing droughts systematically adjust fertility and differ in preferences—for instance, toward firstborn sons. However, a standard quantity–quality trade-off, whereby fewer children are associated with higher educational attainment, does not directly translate into bias here, as identification relies on within-household sibling comparisons. Appendix Table C4 shows no systematic relationship between cumulative exposure to positive or negative productivity shocks since 2000 and the number of school-aged children at the endline survey. In addition, estimates are similar when using community fixed effects instead of household fixed effects, suggesting that any remaining bias from these concerns is limited, as discussed in the robustness checks.

4.3 Effects of productivity shocks during childhood on educational attainment

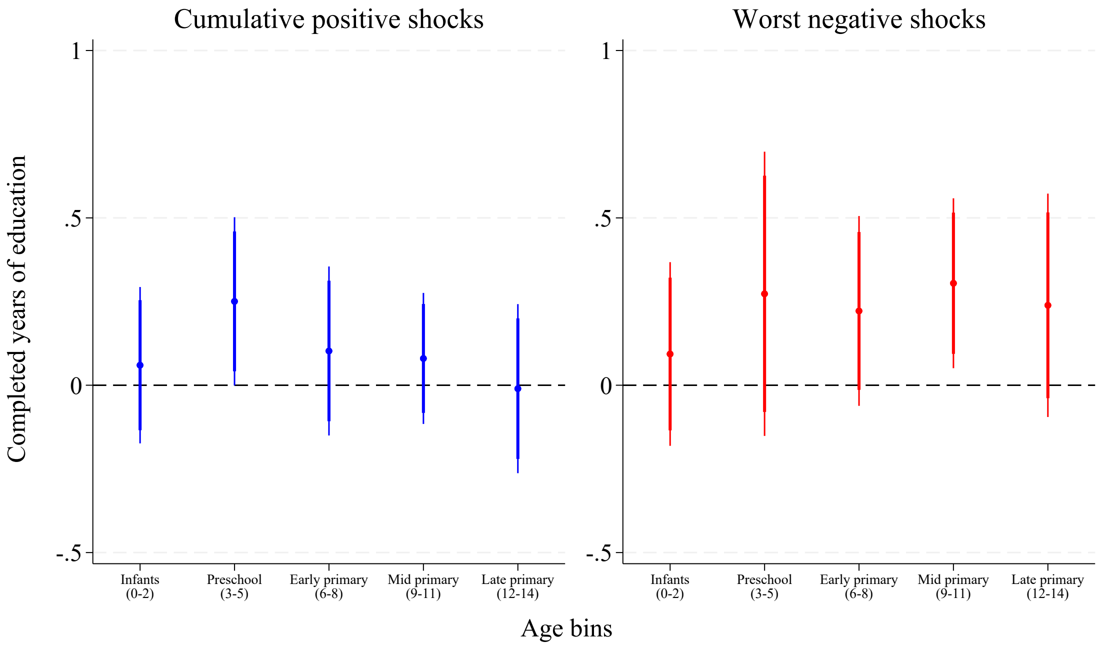
Figure 5, Appendix Table A5, and Appendix Table A6 present the results of positive and negative productivity shocks using regression equation 3.

First, I find that cumulative positive shocks–particularly during the preschool years (ages 3–5)–significantly increase educational attainment in the preferred specification (Column 1 in Appendix Table A5). Specifically, a cumulative one-standard-deviation positive productivity shock, relative to normal years, increases completed years of education by 0.25 years (*p*-value 0.051). While the estimated effects across age bins are not statistically different from one another, the magnitude is largest and statistically significant only during the preschool period. The joint test of positive shocks across all the childhood is also not statistically significant (*p*-value 0.354). These findings are consistent with the human capital literature showing that positive income shocks early in life lead to higher human capital investment (Maccini and Yang, 2009). In addition, point estimates are generally positive from infancy through mid-primary school age, although they are not statistically different from zero in other periods.

Second, negative shocks during the mid-primary school years significantly *increase* educational attainment. Specifically, a one-standard-deviation worst negative productivity shock, relative to normal years, increases completed years of education by 0.30 years (*p*-value = 0.022) in my preferred specification in Column 1 in Appendix Table A8. This period typically coincides with the ages at which children are most at risk of dropping out of school.[36] Rather than directly encouraging school attendance, negative shocks appear to keep children in school by reducing within-

[36] Appendix Figure A12 illustrates the share of children in age-appropriate grades at the time of the endline survey. These are cross-sectional and therefore suggestive patterns. There are noticeable declines between ages 7 and 15, indicating that children either drop out of school or fall behind grade-for-age during primary school, regardless of their current grade. Notably, the timing of these declines aligns with the estimated effects.

Figure 5: Effects of productivity shocks at different stages of childhood



Notes: The figure presents the estimated effects of the censored z-score NDVI at different age bins in early life (up to age 14) on completed years of education. The left figure shows the effects of cumulative positive censored z-score NDVI buffered around 5km for each household location, while the right figure shows the effects of worst negative censored z-score NDVI buffered around 15km for each household location for each age bin. The dots indicate the point estimates, and the thicker line represents the 90% confidence interval, while the thinner line shows the 95% confidence interval of the estimates. The dependent variable, "Completed years of education," is measured at the time of the endline survey in Kenya (2020) and Ethiopia (2022). The age groups correspond to the following periods: "Infants" (ages 0–2), "Preschoolers" (ages 3–5), "Early primary" (ages 6–8), "Mid primary" (ages 9–11), and "Late primary" (ages 12–14). The analysis includes household fixed effects and birth-year fixed effects. Control variables include gender, age, birth order dummies for each child. Standard errors are clustered at the community level. The data covers 3,748 individuals aged 6–20 in Kenya and children aged 7-17 in Ethiopia at the time of the endline survey.

household demand for child labor – at a time when children are otherwise more likely to drop out and begin working. This finding is consistent with interpretations in Atkin (2016) and Shah and Steinberg (2017), which show that increases in the opportunity cost of schooling discourage education. The point estimates for early and late primary school years are similar in magnitude (0.22 and 0.24 years, respectively), although the effects are only marginally insignificant (p-values = 0.13 and 0.16, respectively). The joint test also indicates marginally insignificant effects across all the childhood periods with p-value of 0.103. As with the positive shocks, these estimates do not differ statistically from one another.

Additionally, the type of shocks, whether that is cumulative or not, appears to matter as well. In Appendix Table A7 and Appendix Table A8, I estimate the effects of best positive shocks and cumulative negative shocks, respectively. The results show a robust pattern where the point estimates are similar as in the main tables, but there are some differences. First, the observed effects of best shock during preschool ages increases completed years of education by .223 years (p-value=0.106). The magnitude is similar to the one for cumulative shocks. The results are statistcally significant in Columns 3 and 4, when not controlling for cohort fixed effect or household fixed effects, respectively. Second, I observe a similar positive coefficient (0.210) during mid-primary school age (p-value=0.201), though the effect is not statistically significant when considering cumulative shocks. These seem to highlight an interesting difference in terms of timing and nature of shocks: positive shocks particularly when cumulative during pre-school ages matter, while negative shocks not necesarily consecutive may matter during primary school ages.

4.4 Robustness checks

To assess robustness, I conduct a series of robustness checks and sensitivity analyses. First, Columns 2–4 of Appendix Table A5 and Appendix Table A6 report specifications that exclude control variables (Column 2), drop cohort fixed effects (Column 3), and replace household fixed effects with community fixed effects (Column 4). Across these specifications, the results qualitatively support the main findings, with similar magnitudes and patterns of statistical significance. In particular, cumulative positive shocks during the preschool years are associated with increases in completed years of education of approximately 0.25 to 0.27 years. One exception arises in the specification with community fixed effects, where the estimated magnitude is smaller (0.149), likely because sibling comparisons under household fixed effects amplify the estimated effects. The results for negative shocks exhibit a similar pattern, with estimated increases in educational attainment ranging from 0.230 to 0.301 years. Although the effect is slightly smaller and marginally insignificant in Column 4 (p-value = 0.115), the qualitative conclusions remain unchanged.

Second, I show if the imputation of missing information in the location may bias the results. There may be a concern about the missing information about the future shocks. For example, a child who is 8 years old in the endline has missing values for the shocks between age 9-11. In the preferred specification, I followed the method Zhao and Ding (2024) to impute this value as zero. Here I show the results without imputing, but focusing on the subsamples whose age is older than the time of the shocks. In the preferred approach, I effectively control for the missing values by including missing dummies (which is absorbed by household fixed effects). In Appendix Table A9 and Appendix Table A10, Column 1-2 use the all the samples with imputation while Columns 3-10 restrict the sample children whose age is equal to or above the age at shocks. To assess the sensitivity of this assumption, I restrict samples to individual older than the time of the shocks.

Note that with household fixed effects, the comparison becomes even more restrictive in addition to the limited sample size, as the sibling to compare can be missing, and thus I also show the results with community fixed effects. The results seem to be robust for the positive shocks. The results on the shocks around pre-school ages remain similar in magnitude from .15 to .43 depending on the specification, except for Column 9 where the sample size and comparison is very limited. The coefficients are also positive and similar in magnitude for negative shocks during mid primary age although the effects are imprecisely estimated with the specification of very limited sample size as expected.

Finally, I show the sensitivity of the results based on the different buffer size. As discussed, pastoralists typically graze base location near the community if the condition is normal, while they may need to migrate seasonally up to 15-20km during drought priods (Liao et al., 2017). The discussion in Appendix B yields the preferred buffer sizes which predict the livestock mortality the best. Appendix Table A11-A12 present robustness checks using different buffer sizes to define productivity shocks. Each column shows the set of coefficients from the main regression, with buffer sizes of 5 km, 10 km, 15 km, and 20 km, respectively. The results show consistent estimates across different buffer sizes. The results show the expected patterns: the effects are similar across different buffer sizes, but it becomes imprecise as it increases the buffer sizes for the positive shocks. Similar story goes for the negative shocks where I see similar effects even if I use the smaller buffer sizes, although the effect becomes smaller and imprecise if I use too small buffer, as expected.

5 Mechanism

This section explores the mechanisms underlying the main findings, with a particular focus on the demand for child labor and income effects which leads to the long-term implications the main findings observed, following Section 3. The previous section confirmed that productivity shocks are significantly associated with reported livestock losses. Specifically, negative shocks correspond to reported losses of 3.4–3.7 CMVE, which is approximately equivalent to 21–23 goats or sheep, 2.1–2.3 camels, or 3.4–3.7 cattle. The analysis proceeds with three key components: (i) short-term response of child time use, (ii) heterogeneity by gender, and (iii) age-specific effects during preschool years.

5.1 Demand for child labor vs. income effects

To examine how children's time use responds to productivity shocks, I utilize a household panel survey. I estimate the effects of both lagged and current exposure to productivity shocks on children's time allocation in the concurrent year. Specifically,

$$y_{chjr} = \sum_{b} \sum_{t=y-1,y} \zeta_{b,t} \mathbb{1}\{\text{Binned age} = b\} \times (\theta_t^- + \theta_t^+) + \gamma_j + \phi_r + \varepsilon_{chjr} \tag{4}$$

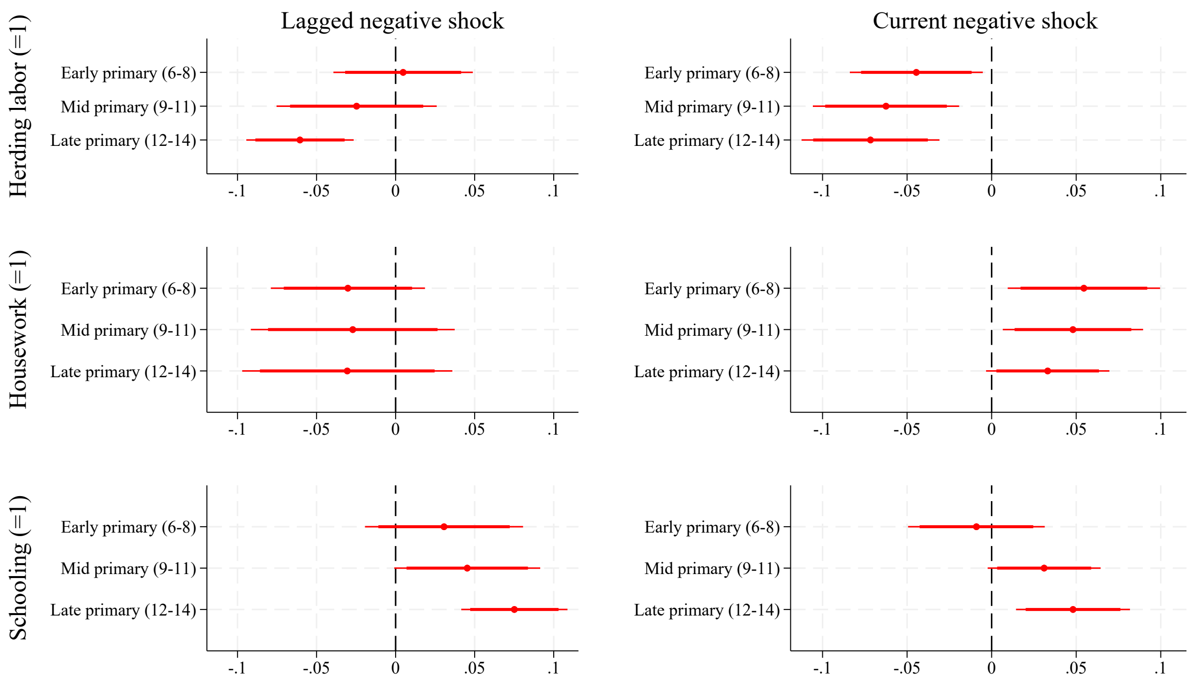
where the outcome variable y_{chjr} is a dummy indicating each child's time use activity (working with livestock, performing housework, or attending school) for child c in household h within community j at round r in year y. θ_t captures the censored z-score NDVI in year t defined as in previous section. The set of coefficients of interest, $\zeta_{b,t}$, capture the effects of current and lagged shocks on children's time use, respectively.

Figure 6 and Appendix Table A13 present the results, revealing an important link between negative productivity shocks and subsequent changes in child labor and schooling. In particular, negative shocks are significantly associated with reductions in the probability of engaging in herding labor, and these effects persist over time. Current negative shocks significantly reduce the probability of herding by 4.5–7.2 percentage points during the primary school ages. Moreover, the effect persists for children aged 12–14, with a reduction of 6.0 percentage points in the following year (p-value = 0.001). These results are robust when using household fixed effects or cluster standard errors at the household level (Appendix Table A14 and Appendix Table A15). Appendix Figures A14 and A15 and Appendix Tables A16 and A17 show the results by gender, and confirm that the education gain happens for older male with a mirroring decrease in herding labor in the lag although female late primary group also benefited. Interestingly, although current negative shock increases the probability of housework, it does not have the effect with a lag.

By contrast, negative shocks are associated with statistically significant increases in the probability of attending school (Column 3), both contemporaneously and with a lag. Specifically, a one-standard-deviation current negative shock increases the probability of schooling by 4.5 and 7.5 percentage points for children aged 9–11 and 12–14, respectively. These effects persist into the following year, with increases of 3.1 and 4.8 percentage points for mid-primary and late-primary ages, respectively (p-values = 0.067 and = 0.007). In contrast, effects for early primary ages (6–8) are not statistically significant.

These findings contrast with Ponnusamy (2026), who show that positive rainfall shocks reduce school attendance and increase labor participation among older children. In addition, while cur-

Figure 6: Effects of current and lagged negative productivity shocks on child time use



Notes: The figures present estimated effects of negative productivity shocks at different age bins during the primary school period – in the lagged year and the current year – on children's time use. The left column of panels shows lagged effects, while the right column shows contemporaneous effects. The top row reports effects on herding labor, the middle row on housework, and the bottom row on schooling. Time use is measured in each wave of the panel household surveys conducted in Kenya in 2009, 2010, 2011, 2012, 2013, 2015, and 2020, and in Ethiopia in 2012, 2013, 2014, 2015, and 2022. Outcome variables are binary indicators for whether a child engages in herding labor, performs housework, or attends school, based on reported primary and secondary activities. Points denote point estimates; thick lines indicate 90 percent confidence intervals, and thin lines indicate 95 percent confidence intervals.

rent negative shocks significantly increase the probability of housework among children in early and mid-primary school–consistent with Son (2025)–these effects do not persist for lagged shocks. Taken together, the results support the interpretation that negative productivity shocks lead to livestock losses, thereby reducing subsequent child labor demand in animal husbandry, particularly among older children, which leads to a long-run increase in educational attainment.

Next, I examine the heterogeneity by child gender, motivated by the distinct roles and tasks typically assigned to boys and girls. As highlighted in Section 3, boys are more likely to engage in livestock-related work such as herding, while girls tend to assist with housework. Productivity shocks are expected to directly affect boys by altering labor demand in livestock production. Therefore, if the observed effects are primarily driven by changes in child labor demand in animal husbandry, they should predominantly impact boys. Conversely, if the results are more closely related to income effects, there should be no significant gender differences–or potentially slightly larger effects for girls–given the higher returns to education for females (Psacharopoulos, 1994; Villa, Barrett, and Just, 2011).

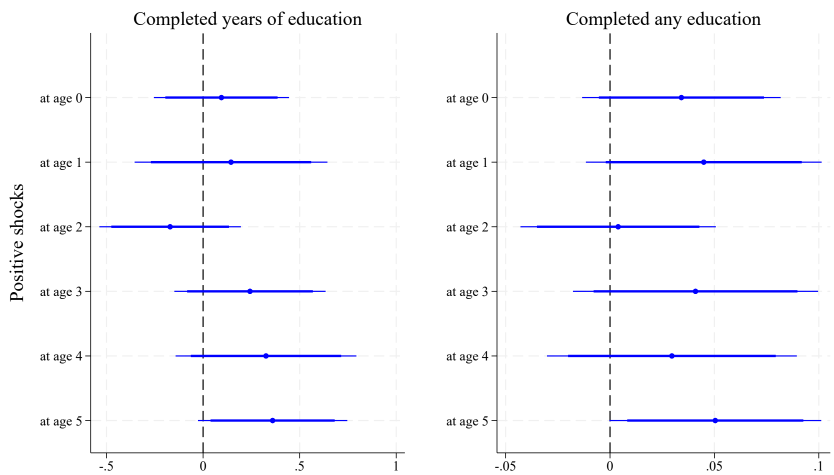
Figure A17 presents the heterogeneous effects by gender across different timings of productivity shocks. As in the main results, cumulative positive shocks are shown on the left, while the worst negative shocks are shown on the right. Consistent with the hypothesis that the observed positive effects during ages 3–5 are driven purely by income effects, there are no statistically significant differences between boys and girls. The coefficient for boys is 0.20 with a p-value of 0.15, while the difference in point estimates between genders is 0.11 with a p-value of 0.24. However, the effects appear to be more pronounced for girls, with a coefficient of 0.31 during that age group and a p-value of 0.019. This is consistent with the broader idea that female has higher returns to education globally (Psacharopoulos, 1994).

However, for the most severe negative shocks, particularly around mid-primary age (9–11), as well as similar effects observed from early to late primary age, the impact appears to be only for boys. The coefficient estimates for boys are statistically significant, with p-values of 0.049, 0.019, and 0.082 for early primary, mid-primary, and late primary ages, respectively, although I cannot reject the null hypothesis that these effects are statistically different from those for girls, as the p-value for the interaction term during mid-primary age is 0.540. This may be partly due to non-separability, where girls are also indirectly affected through an increased burden of household tasks during periods of hardship. Given the gendered nature of tasks in this context (Son, 2025), this mirrors findings from other studies showing that children facing higher labor demand are more likely to drop out when economic opportunities increase (Shah and Steinberg, 2017; Atkin, 2016). My finding is in line with Björkman-Nyqvist (2013), who found that Ugandan households adjust girls' schooling and resources in response to rainfall-induced income shocks, while boys are largely sheltered.

Next, I turn to the income-effect channel. Conceptually, positive productivity shocks increase livestock productivity and thereby boost household income. However, quantifying this channel is particularly challenging in pastoralist contexts, where both wealth and income are largely held in the form of in-kind livestock assets, and where the main income source—milk—is inherently noisy (Barrett et al., 2025). Despite these challenges, I examine how current and lagged productivity shocks affect income. Appendix Table A20 shows that, although the estimates are imprecise, both current and lagged positive shocks are consistently associated with higher milk income. In contrast, lagged negative shocks increase cash earnings, while contemporaneous negative shocks reduce them, though the magnitudes are economically small. This pattern likely reflects household adjustment behavior in a setting with thin labor markets: households experience income losses in the shock year, but subsequently attempt to generate additional cash income in the following year to compensate for earlier losses.

Now, I turn to estimating the effects of age-specific productivity shocks to explore the income channel at the critical moments. I modify the binned age specification of regression equation 3 by incorporating the age at which the shock occurred. I report the effects of productivity shocks during preschool years on educational attainment.[37]

Figure 7: Effects of positive productivity shocks during preschool age



Notes: The figures present estimated effects of the censored z-score NDVI at different ages during pre-school age (0-5) on educational attainment. The dependent variables, "Completed years of education" and "Completed any schooling" are measured at the time of the endline survey in Kenya (2020) and Ethiopia (2022). The latter is a dummy taking a value one if a child completes any education. Control variables includes shocks during school age, gender, age, birth order dummies for each child, the number of school-aged children, and livestock holdings in CMVE. Birth-year fixed effects control for age-specific dummies, and household fixed effects are dummies for each household. Standard errors are clustered at the community level.

Figure 7 and Appendix Table A19 report the estimates. I present the effects on completed years of education, as well as on whether a child has completed any schooling, while controlling for school-age shocks during ages 6-14. They provide evidence that positive productivity shocks at age 5, just before the primary school entry age, significantly increase total years of completed education, primarily by raising the probability of any schooling. Specifically, a one-standard-deviation positive shock at age 5 increases completed years of education by 0.36 years (p-value =

[37]More specifically, I estimate the following regression equation for an individual i in household h, residing in location j, and born in year t:

$$S_{ihjt} = \sum_{a=0}^{14} \zeta_b \theta_{h,a} + \lambda_h + \phi_t + \mathbf{X}'_{ih}\beta + \varepsilon_{ihjt} \tag{5}$$

0.067). Additionally, such a shock increases the probability of completing any schooling by 5.0 percentage points (p-value = 0.052). This suggests that the effects may be driven by the relaxation of short-term credit constraints at the critical moment when households decide whether to enroll their children in primary school. This can be interpreted as households are liquidity constrained for sending children school. This mirrors the findings of Nübler et al. (2021), which reported that negative rainfall shocks reduce enrollment and educational attainment, particularly at ages when children are expected to start primary school.

These findings are consistent with Maccini and Yang (2009), which demonstrates that early-life positive income shocks lead to better human capital accumulation. Our results underscore the importance of timing: positive income shocks occurring just before the start of primary school are critical for the decision to attend school. The effects appear to be primarily driven by the relaxation of short-term liquidity constraints, yet this impact persists into completed years of education. Furthermore, the effect seems to be primarily driven by the extensive margin—whether a child enters primary school or not.

The observed positive effects during preschool age align with the interpretation that increased income helps households cover the financial costs of schooling. This effect does not differ significantly by child gender. In contrast, the effects observed during mid-primary school ages, particularly for boys, are driven by a reduction in their opportunity cost of schooling, allowing them to remain enrolled for longer. This effect is not observed for girls, as the demand for their labor experiences smaller changes.

One may ask why positive productivity shocks do not increase child labor demand to the same extent. There are three possible explanations for this asymmetry. First, as discussed earlier, children typically begin working between ages 7 and 10, implying that positive shocks occurring at younger ages (e.g., around age 5) may be too early to translate into increased child labor demand. Consistent with this, Appendix Figure A16 and Appendix Table A18 show that positive shocks have no significant contemporaneous effects on child time use, including herding, while lagged positive shocks increase the probability of herding only among older children, but not among younger children aged 6–8 without decreasing schooling. This implies that after the good periods, older children may be demanded, but in a different way from drought in a sense that they can still combine with schooling. Second, many households in this setting appear to be budget constrained and to underinvest in education. As a result, positive shocks can relax liquidity constraints and increase schooling, whereas negative shocks do not necessarily reduce educational investment symmetrically. Third, positive shocks may raise household income without increasing the demand for child labor. During favorable years, pastoralists may benefit from higher productivity such as increased milk yields. In such cases, income rises without a corresponding increase in labor requirements, limiting the response of child labor demand.

5.2 Other potential channels: migration, conflict, nutrition

Productivity shocks may influence grazing and herd migration, which in turn could affect educational decisions. Toth (2015) show that the likelihood of migration is a function of herd size among northern Kenyan pastoralists. Consistent with Liao et al. (2017), the drier environmental conditions common in this region often compel pastoralists to utilize rangelands far from their base camps. The impact of such forced migration due to droughts on education is likely negative: if children migrate with their households to satellite camps to care for livestock, attending school regularly becomes more difficult. In the main specification, household fixed effects help address this concern, as they absorb household-level migration dynamics.

Appendix Table A21 presents the effects of productivity shocks on household settlement status. The results indicate that current negative productivity shocks reduce the probability of being fully settled, as expected, since pastoralists often need to move further to access rangelands. However, the effects of lagged shocks are in the opposite direction: past negative productivity shocks increase the likelihood of being fully settled. This finding aligns with Toth (2015), who suggest that previous shocks reduce livestock holdings, thereby discouraging migration in subsequent periods. These results are consistent with and may reinforce the child labor mechanism: current shocks lead to increased mobility and greater demand for child labor, while past shocks–by reducing herd size–lead to more permanent settlement, reduced child labor demand, and improved educational outcomes over the longer term.

Another possible explanation for improved educational outcomes following droughts is an income effect through livestock raiding. In this context, some households may occasionally engage in raiding–stealing livestock from other households or ethnic groups–and selling the animals for cash (Jensen et al., 2025). A concern is that negative shocks could increase both migration and conflict, potentially raising household income and thus educational investment. However, this mechanism is unlikely to explain the main findings. First, I observe migration increase only in the current year, but not in the following year, which should not lead to the observed effect on educational attainment. Second, livestock losses due to raiding, rustling, or conflict are relatively rare–averaging 0.034 events per year, or about 1% of all loss events over the past 20 years.

Final potential mechanism is through nutrition. Positive (negative) productivity shocks may improve (worsen) child nutrition as part of the income effect. However, two points suggest this is not the main channel. First, nutrition is known to be particularly critical in the first 1,000 days of life (up to around age two), yet I do not find statistically significant effects during that period in Figure 7. Second, in this setting, school meals are provided for free, so children not benefiting from positive shocks may have a stronger incentive to attend school for food–implying the opposite pattern of what I find. For the droughts, one might concern that the food aid comes as school meal. If school meal is provided for all cohorts, it is absorbed in household FE. If only additionally provided priority to younger, for example, the effects are likely to be lower bound, as I find the increase of education of older relative to younger cohort upon droughts.

6 Conclusion and policy implication

Child labor remains widespread in the developing world, often limiting children's educational attainment due to the high opportunity cost of schooling, particularly in agriculture. This paper shed light on within household child labor in agriculture, and examines how shocks on productive asset influence educational attainment and child labor in pastoralist communities in ASALs of Kenya and Ethiopia, where livestock assets generate demand for child labor. By combining household survey data with a 20-year history of NDVI-based rangeland health measures, I exploit quasi-random spatial and temporal variation in livestock production to estimate the effects of shocks during childhood on educational attainment. The results reveal an interesting heterogeneous effeects of shocks by child age and gender, showing income effects dominate at early ages, when child labor is uncommon, while at older ages the child labor channgel becomes more salient, especially for boys, who bear a greater share of herding labor.

These results suggest that both income effects and child labor demand effects play important roles during critical developmental periods, particularly in settings where household production and child labor are closely linked. Exposure to droughts reduces subsequent child labor demand by destroying livestock holdings, a dynamic likely reinforced by subsequent decreases in migration. Positive shocks appear to benefit both boys and girls equally, while the effects of negative shocks are concentrated among boys, who are more directly involved in herding labor. Together, these patterns underscore how the opportunity cost of schooling–shaped by household production needs and gendered labor roles–affects human capital investment in agricultural households. Overall, this study contributes to the literature on human capital development in the presence of child labor by emphasizing the need to account for both income effects and opportunity cost dynamics in households where children actively participate in production.

This paper has a large implications on 268 million pastoralists in the drylands of Africa, providing 70% of Africa's milk and meat. But it is not limited to them but it is likely to be relevant across many poor households in the developing world , as most rely on small-scale farming (World Bank, 2008) and have thin labor markets. Two key features define the setting of this study: first, child labor is closely tied to household productive assets; and second, external labor markets are thin or absent. While the specific effects of productivity shocks are likely to be context-dependent–particularly depending on whether child labor is a complement to or substitute for productive assets–the broader framework provides insight into how household production constraints shape educational decisions.

The findings offer valuable guidance for policymakers seeking to improve educational outcomes in regions frequently exposed to climatic and economic shocks, particularly where the risk of child labor is high. This research shows how early-life economic conditions interact with intra-household labor dynamics to shape both schooling and child labor trajectories in non-separable households. Three policy implications follow. First, the positive effects of productivity shocks during preschool years highlight the importance of targeted financial interventions–such as cash transfers–around the time of school entry to ease liquidity constraints. However, such programs must be carefully designed to avoid unintended consequences: in-kind transfers like livestock may raise the opportunity cost of schooling and increase child labor demand, thereby harming education (Edmonds and Theoharides, 2020). Second, because negative shocks can reduce child labor demand by limiting household production, it is critical to buffer households against income losses through instruments such as agricultural insurance, particularly during school-age years when children are most at risk of being withdrawn from school (Son, 2025; Barrett et al., 2025). Third, improving school access is essential for vulnerable populations. For remote and mobile pastoralists, expanding mobile schooling can lower the cost of education, while boarding school options can help children continue attending during periods of seasonal migration. Complementary programs, such as providing school meals, can further encourage enrollment and regular attendance.

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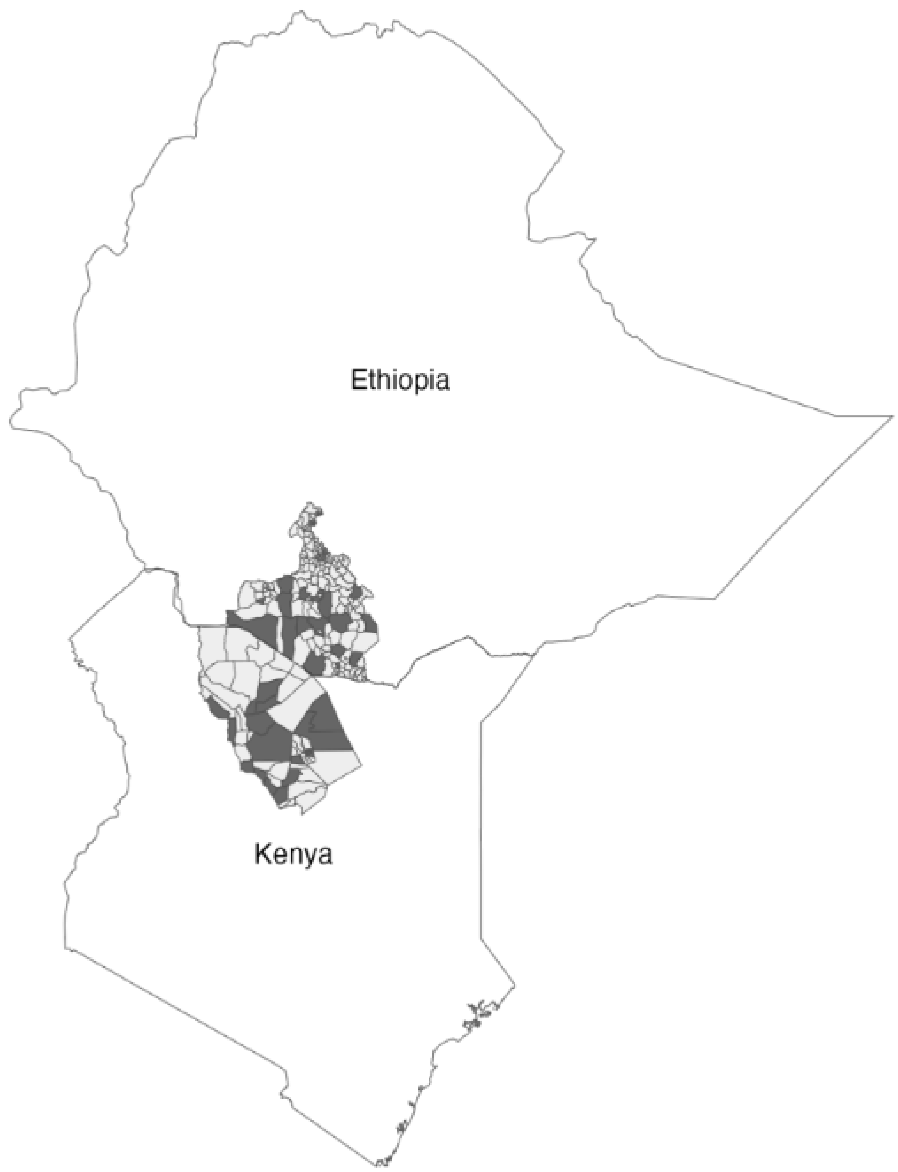
Appendix

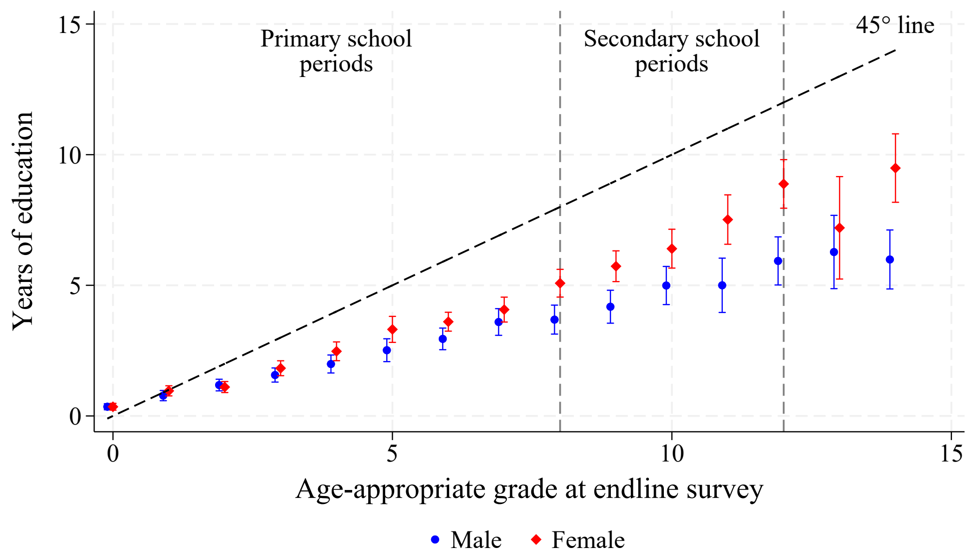
A Figures and Tables

Figure A1: Map of Study Locations



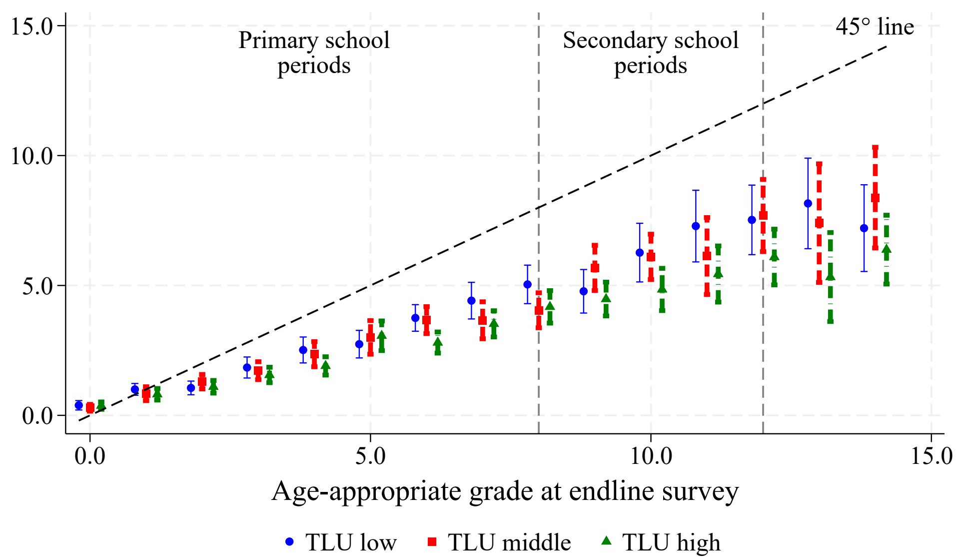
Notes: This map shows the 33 study locations in dark grey, corresponding to sublocations in Kenya and kebeles in Ethiopia. The map is based on Figure 1 in Barrett et al. (2025). See the codebooks for additional details. Data sources are available at `https://data.ilri.org/portal/dataset/ibli-marsabit-r1` (Marsabit) and `https://data.ilri.org/portal/dataset/ibli-borena-r1` (Borena).

Figure A2: Completed years of education across age by gender



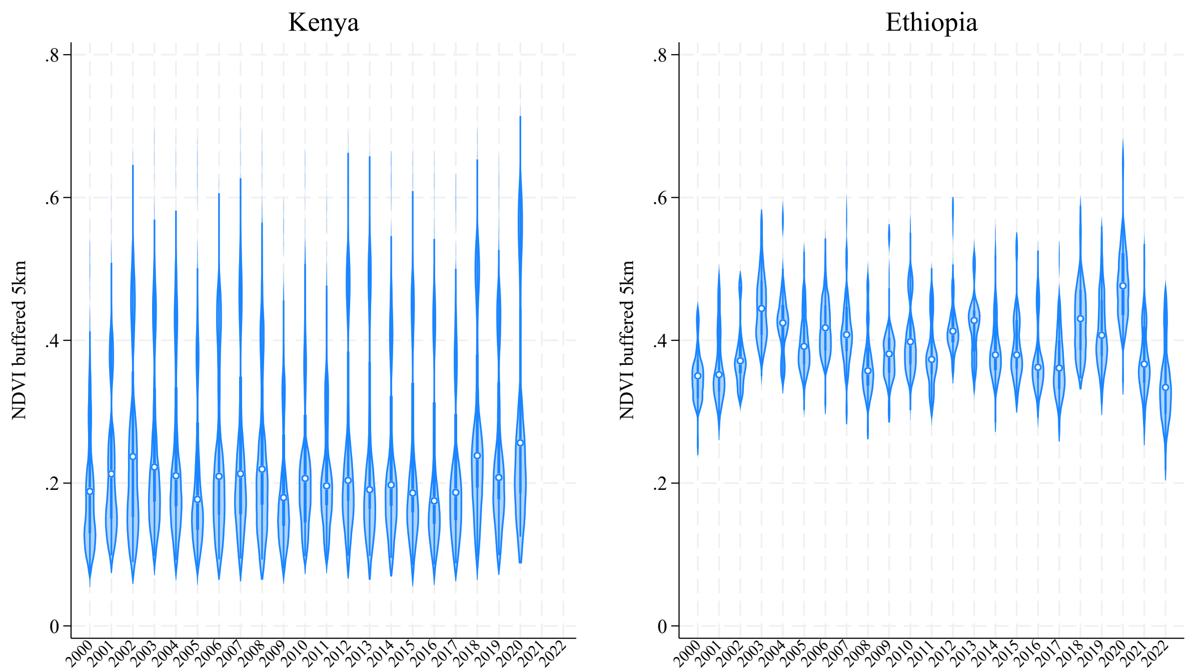
Notes: This figure shows the average completed years of education at each age, relative to ages six and seven in Kenya and Ethiopia, respectively, by gender. The x-axis, labeled "Age-appropriate grade at endline survey," is normalized separately for each country: it represents age at endline minus 6 in Kenya and minus 7 in Ethiopia, so that zero corresponds to the age at the start of primary schooling. Points indicate means, and vertical lines represent 95% confidence intervals. The 45-degree line denotes age-appropriate educational attainment, where each year of schooling corresponds to the expected grade level for a child of a given age. The sample is restricted to individuals aged 6–20 in Kenya and 7–17 in Ethiopia, as observed in the 2020 R7 survey for Kenya and the 2022 R5 survey for Ethiopia.

Figure A3: Completed years of education across age by herd size



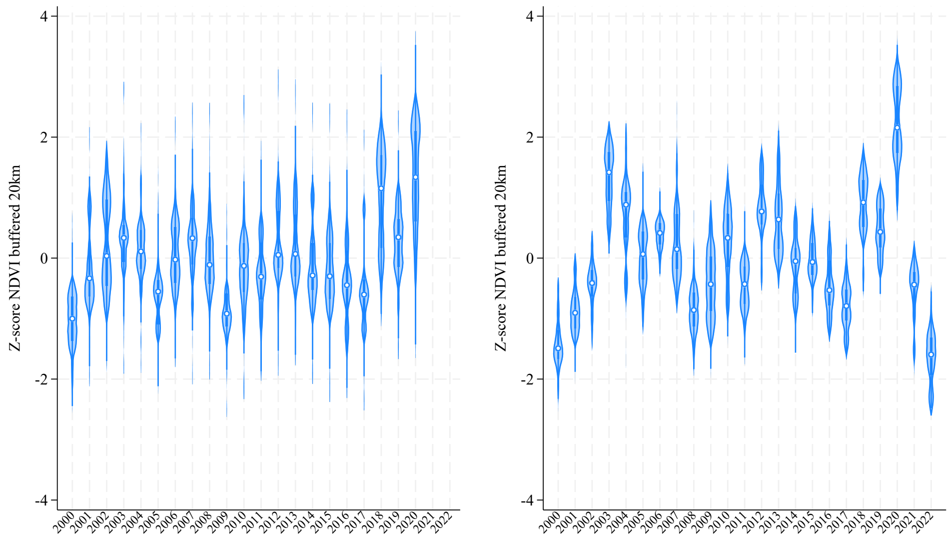
Notes: These figures show the average completed years of education at each age, relative to ages six and seven in Kenya and Ethiopia, respectively, by baseline herd size measured in tropical livestock units (TLU). Baseline herd size is measured in the 2009 survey for Kenya and the 2012 survey for Ethiopia. TLU categories are defined as follows: low (less than 5 TLU), middle (5–15 TLU), and high (more than 15 TLU). The x-axis, labeled "Age-appropriate grade at endline survey," is normalized separately for each country: it represents age at endline minus 6 in Kenya and minus 7 in Ethiopia, so that zero corresponds to the age at the start of primary schooling. Points indicate means, and vertical lines represent 95% confidence intervals. The 45-degree line denotes age-appropriate educational attainment, where each year of schooling corresponds to the expected grade level for a child of a given age. The sample is restricted to individuals aged 6–20 in Kenya and 7–17 in Ethiopia, as observed in the 2020 R7 survey for Kenya and the 2022 R5 survey for Ethiopia. One TLU is defined as 1 cattle, 0.7 camels, or 10 sheep/goats.

Figure A4: NDVI distribution during study periods



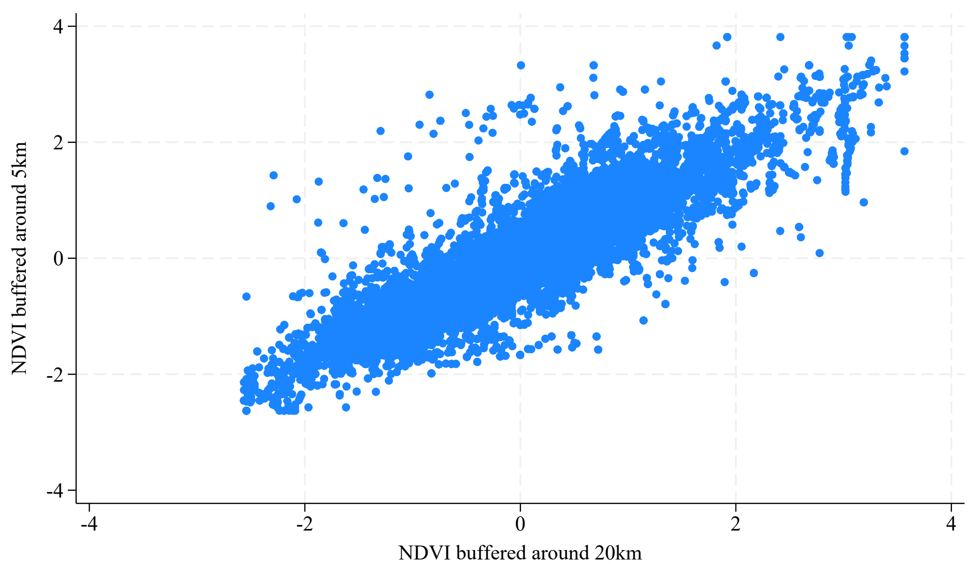
Notes: This figure presents the violin plot of average NDVI buffered around 5km for each sample household since 2000. Pre-survey location information is imputed. Please see B for the details.

Figure A5: z-score NDVI distribution during study periods



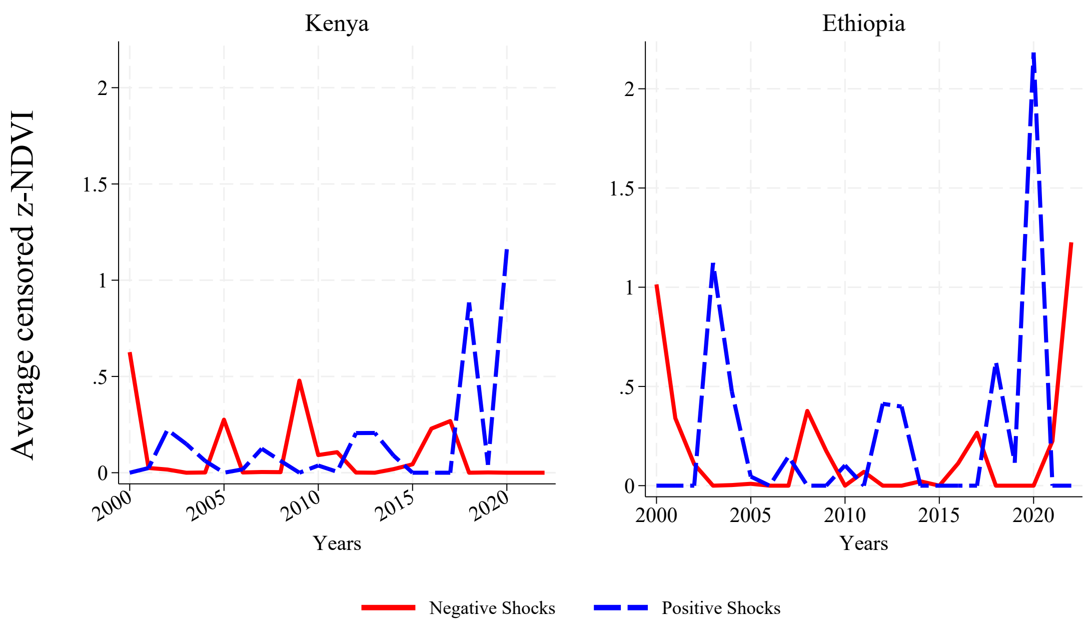
Notes: This figure presents the violin plot of average z-score NDVI buffered around 5km for each sample household since 2000. Pre-survey location information is imputed. Please see B for the details.

Figure A6: Correlation of buffered NDVI



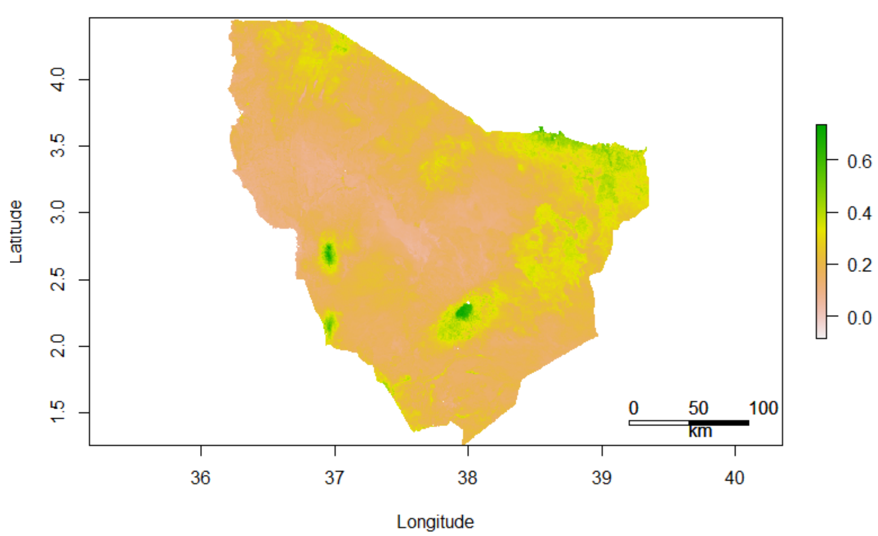
Notes: This figure shows the correlation between NDVI buffered around 5km and buffered around 20km using full year samples.

Figure A7: Temporal variations of productivity shocks



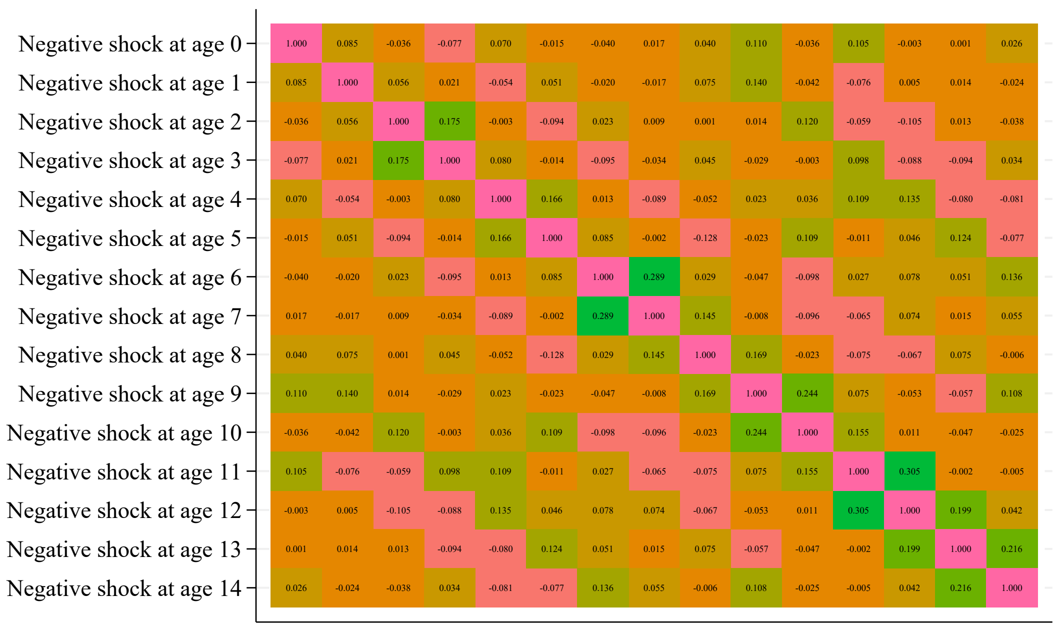
Notes: The figure illustrates the average censored z-score NDVI since 2000 for Kenya and Ethiopia. The red line represents negative shocks, while the blue line represents positive shocks.

Figure A8: Spatial variations of NDVI in 2009



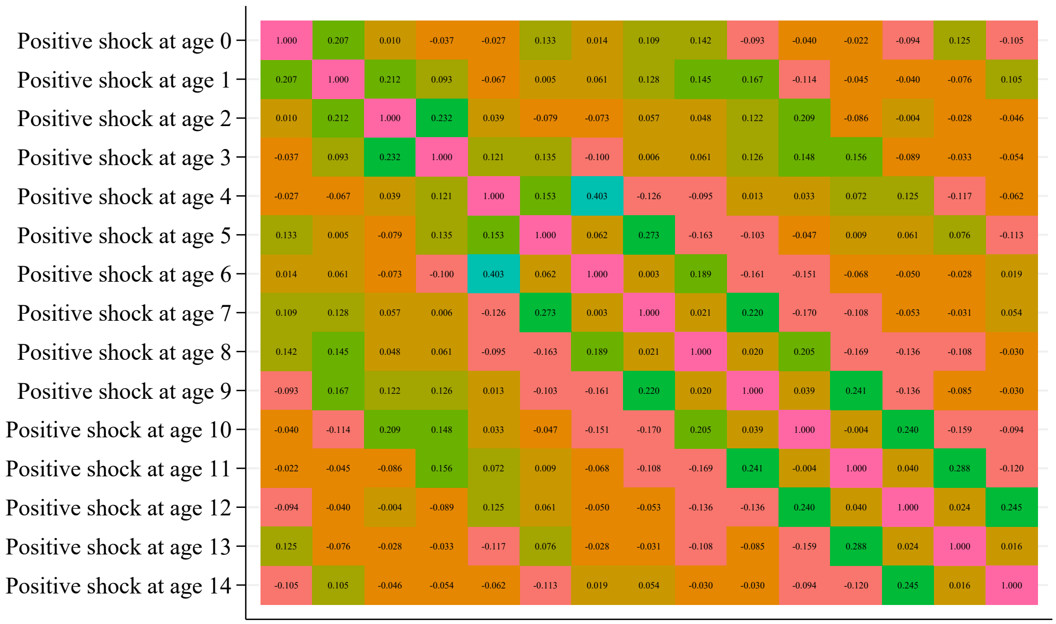
Notes: This figure shows the spatial variations of NDVI in 2009 in one of our study sites (Marsabit district).

Figure A9: Correlation between negative shocks at different ages in the sample



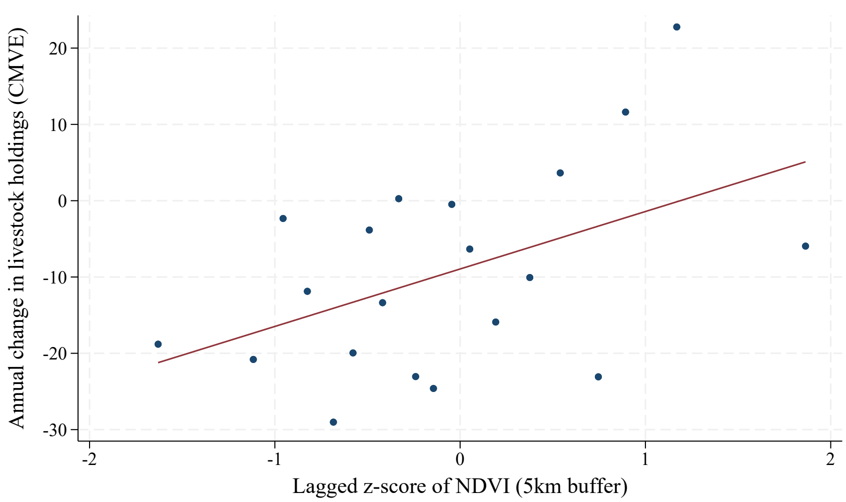
Notes: This describes the correlation matrix for the values of negative shocks at different ages for individual in the sample. The x- and y-axes describe the age of the shock.

Figure A10: Correlation between positive shocks at different ages in the sample



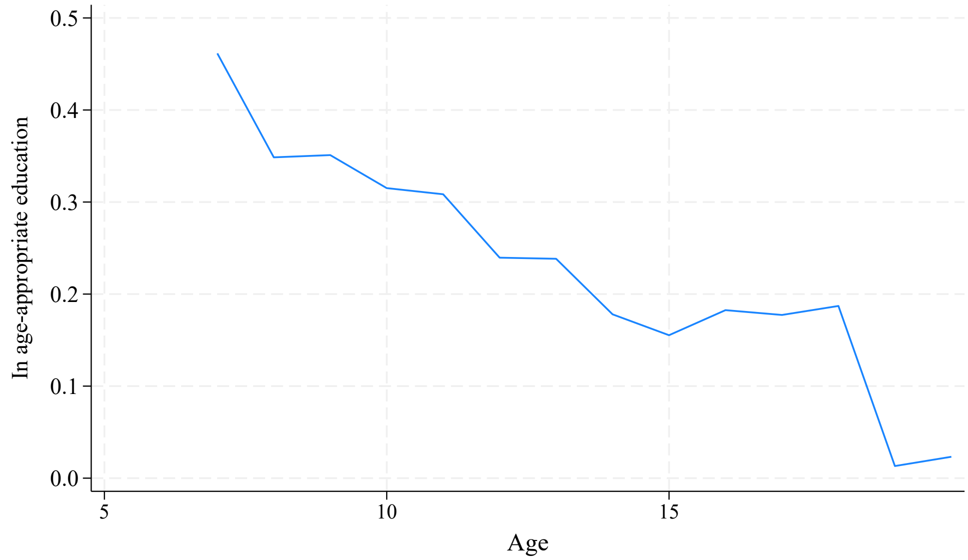
Notes: This describes the correlation matrix for the values of negative shocks at different ages for individual in the sample. The x- and y-axes describe the age of the shock.

Figure A11: Relationship between z-score NDVI and livestock outcomes



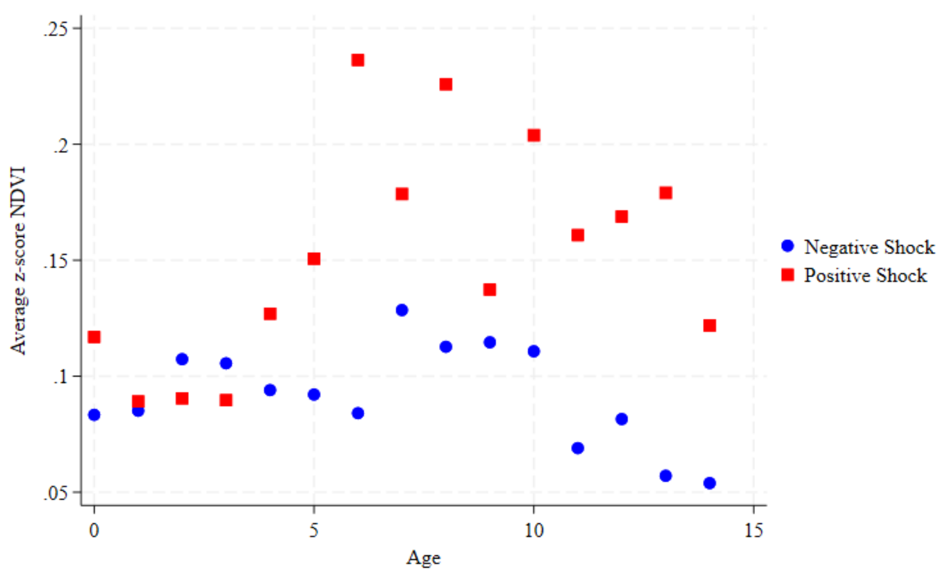
Notes: The figure shows the relationship between the lagged z-score NDVI and annual change in livestock holdings (CMVE). The outcomes are based on the panel household survey.

Figure A12: Share of on-track education (age-appropriate grade) by age



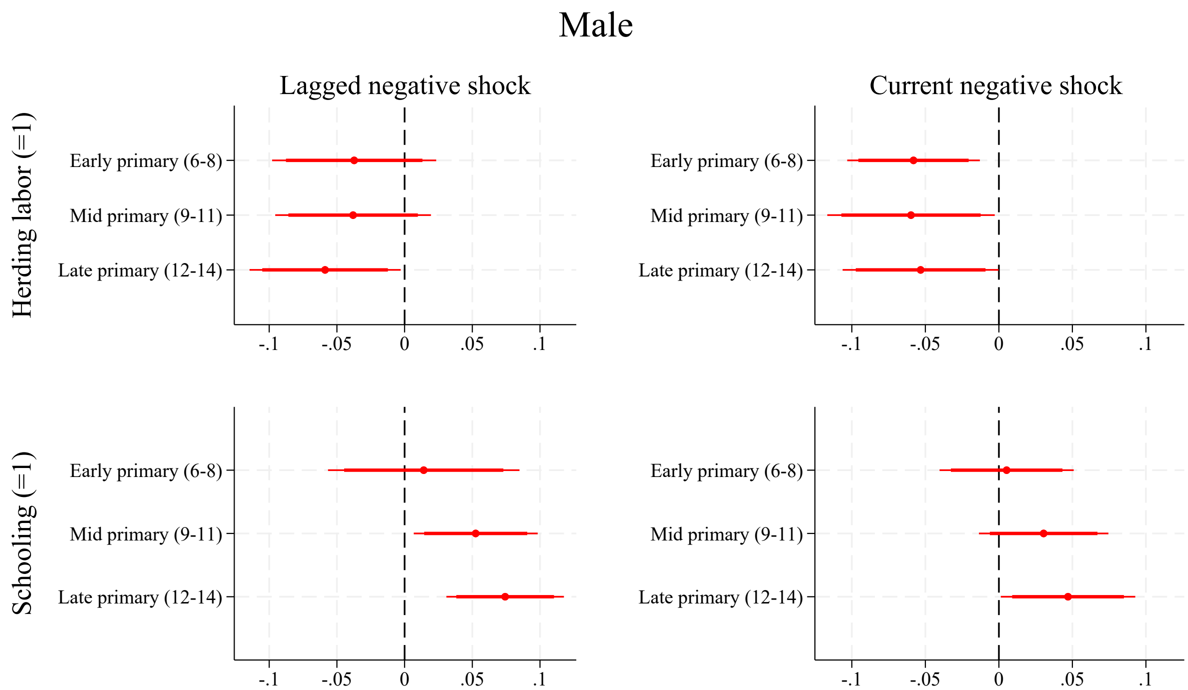
Notes: The sample is restricted to individuals ages from 6 to 20 in Kenya and 7 to 17 in Ethiopia at the endline survey.

Figure A13: Variation of shocks across ages



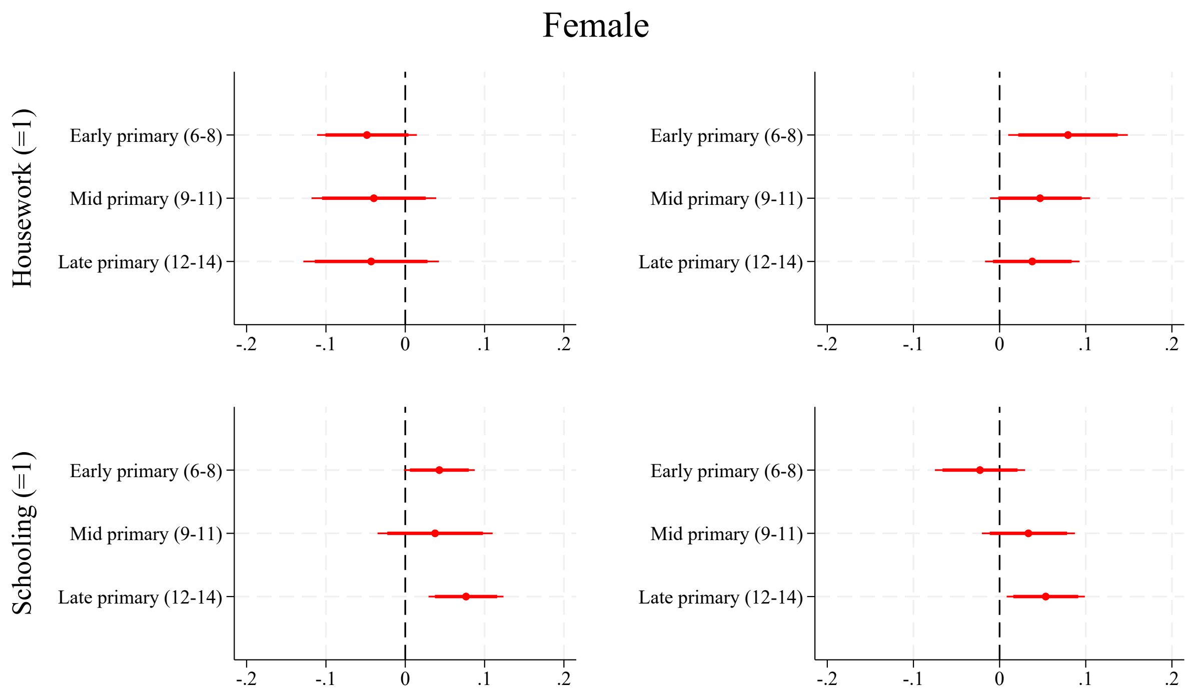
Notes: This figure shows the share of children who experienced negative and positive shocks at each age.

Figure A14: Effects of current and lagged negative productivity shocks on child time use for male



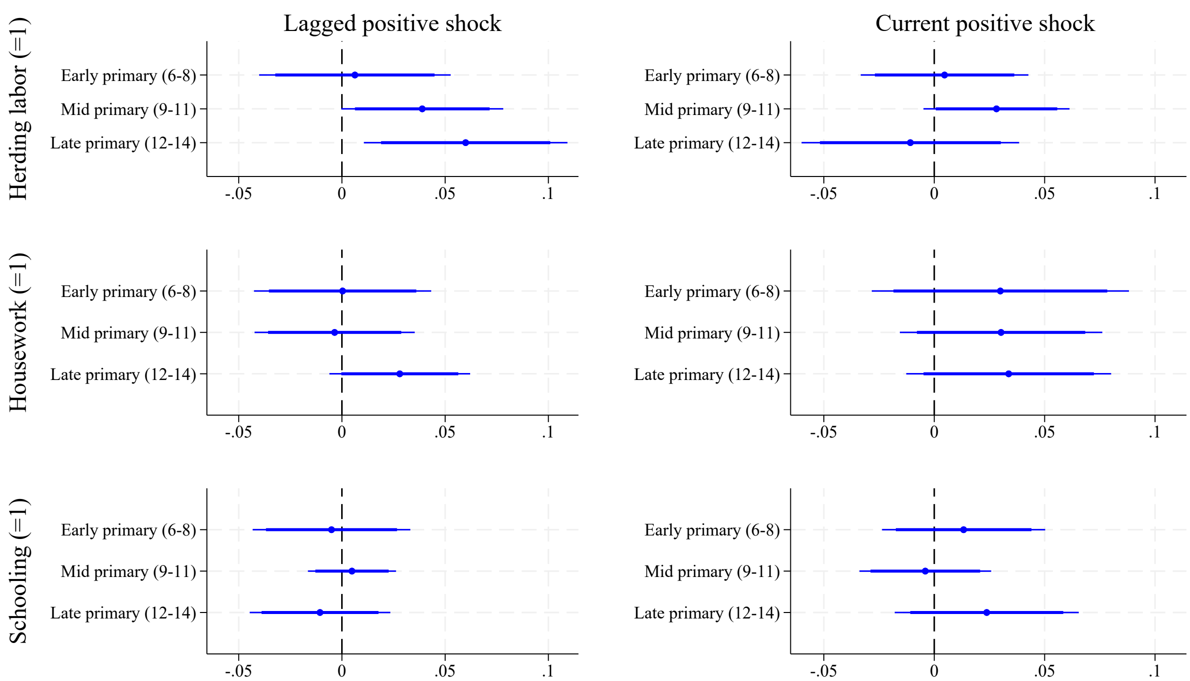
Notes: The figures present estimated effects of negative productivity shocks at different age bins during the primary school period – in the lagged year and the current year – on children's time use. Samples are restricted to male. The left column of panels shows lagged effects, while the right column shows contemporaneous effects. The top row reports effects on herding labor, the middle row on housework, and the bottom row on schooling. Time use is measured in each wave of the panel household surveys conducted in Kenya in 2009, 2010, 2011, 2012, 2013, 2015, and 2020, and in Ethiopia in 2012, 2013, 2014, 2015, and 2022. Outcome variables are binary indicators for whether a child engages in herding labor, performs housework, or attends school, based on reported primary and secondary activities. Points denote point estimates; thick lines indicate 90 percent confidence intervals, and thin lines indicate 95 percent confidence intervals.

Figure A15: Effects of current and lagged negative productivity shocks on child time use for female



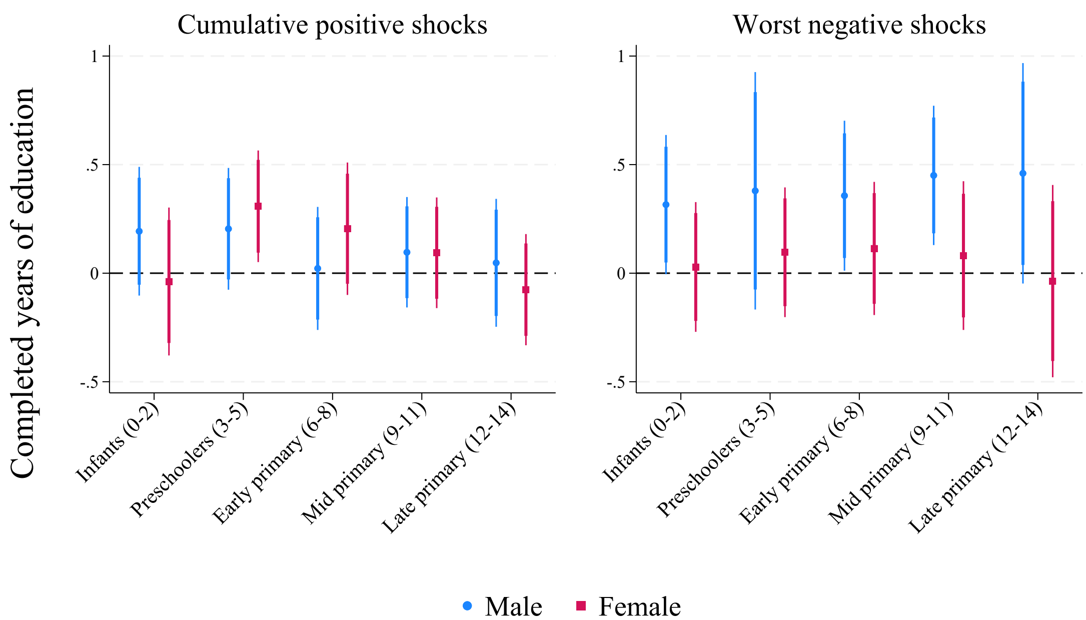
Notes: The figures present estimated effects of negative productivity shocks at different age bins during the primary school period – in the lagged year and the current year – on children's time use. Samples are restricted to female. The left column of panels shows lagged effects, while the right column shows contemporaneous effects. The top row reports effects on herding labor, the middle row on housework, and the bottom row on schooling. Time use is measured in each wave of the panel household surveys conducted in Kenya in 2009, 2010, 2011, 2012, 2013, 2015, and 2020, and in Ethiopia in 2012, 2013, 2014, 2015, and 2022. Outcome variables are binary indicators for whether a child engages in herding labor, performs housework, or attends school, based on reported primary and secondary activities. Points denote point estimates; thick lines indicate 90 percent confidence intervals, and thin lines indicate 95 percent confidence intervals.

Figure A16: Effects of current and lagged positive productivity shocks on child time use



Notes: The figures present estimated effects of positive productivity shocks at different age bins during the primary school period – in the lagged year and the current year – on children's time use. The left column of panels shows lagged effects, while the right column shows contemporaneous effects. The top row reports effects on herding labor, the middle row on housework, and the bottom row on schooling. Time use is measured in each wave of the panel household surveys conducted in Kenya in 2009, 2010, 2011, 2012, 2013, 2015, and 2020, and in Ethiopia in 2012, 2013, 2014, 2015, and 2022. Outcome variables are binary indicators for whether a child engages in herding labor, performs housework, or attends school, based on reported primary and secondary activities. Points denote point estimates; thick lines indicate 90 percent confidence intervals, and thin lines indicate 95 percent confidence intervals.

Figure A17: Heterogeneous effects of productivity shocks by gender of the child



Notes: The figure presents the estimated effects of the censored z-score NDVI at different age bins in early life (up to age 14) on completed years of education by the gender of a child. The left figure shows the effects of cumulative positive censored z-score NDVI buffered around 5km for each household location, while the right figure shows the effects of worst negative censored z-score NDVI buffered around 15km for each household location. The dots indicate the point estimates, and the thicker line represents the 90% confidence interval, while the thinner line shows the 95% confidence interval of the estimates. The dependent variable, "Completed years of education," is measured at the time of the endline survey in Kenya (2020) and Ethiopia (2022). "Cumulative" and "Worst" indicate the nature of productivity shocks experienced during each age bin in childhood. The age groups correspond to the following periods: "Infants" (ages 0–2), "Preschoolers" (ages 3–5), "Early primary" (ages 6–8), "Mid-primary" (ages 9–11), and "Late primary" (ages 12–14). The analysis includes household fixed effects and birth-year fixed effects. Control variables include gender, age, birth order dummies for each child, and the number of school-aged children. Standard errors are clustered at the community level. The data covers 3,748 individuals aged 6–20 in Kenya and children aged 7–17 in Ethiopia at the time of the endline survey.

Table A1: Household level summary statistics

	Mean/SD	Min	P25	Median	P75	Max	Obs
Total livestock holdings (CMVE)	22.64	0.00	4.50	11.08	26.60	416.95	1220
	[32.64]						
Camel holdings (CMVE)	9.08	0.00	0.00	0.00	9.60	299.20	1220
	[20.39]						
Cattle holdings (CMVE)	7.50	0.00	0.00	3.00	9.00	250.00	1220
	[14.76]						
Goat holdings (CMVE)	3.26	0.00	0.64	1.65	4.20	63.00	1220
	[4.58]						
Sheep holdings (CMVE)	2.79	0.00	0.00	0.60	2.85	77.25	1220
	[5.95]						
Livestock lost (CMVE)	10.48	0.00	2.00	5.15	12.50	200.60	1165
	[15.72]						
Cash earnings (USD)	556.97	0.00	106.01	255.98	553.67	10174.53	1152
	[930.48]						
Milk income (USD)	595.50	0.00	0.00	124.75	442.21	11629.81	1152
	[1313.93]						

Notes: This table shows mean and standard deviations (square bracket), minimum, 25 percentile, median, 75 percentile, maximum, and the number of observation for each household characteristics. Cash earnings and milk income is calculated based on USD. The data is from the baseline survey (2009 in Kenya and 2012 in Ethiopia).

Table A2: Summary statistics of control variables by gender

	(1) Full sample Mean/SD	(2) Female Mean/SD	(3) Male Mean/SD	(4) Pairwise t-test Mean/SD
Control variables				
Age	12.16	11.82	12.43	-0.61***
	[3.80]	[3.62]	[3.93]	
Male (= 1)	0.55	0.00	1.00	-1.00
	[0.50]	[0.00]	[0.00]	
First born (=1)	0.33	0.31	0.35	-0.04**
	[0.47]	[0.46]	[0.48]	
Second born (=1)	0.28	0.29	0.28	0.01
	[0.45]	[0.45]	[0.45]	
Third born (=1)	0.19	0.20	0.19	0.01
	[0.39]	[0.40]	[0.39]	
Fourth or more born (=1)	0.20	0.21	0.19	0.02
	[0.40]	[0.41]	[0.39]	
Other variables				
Exists siblings in the sample (=1)	0.95	0.94	0.96	-0.02*
	[0.21]	[0.23]	[0.19]	
# siblings in the sample (incl self).	3.76	3.78	3.73	0.05
	[1.53]	[1.56]	[1.50]	
Observations	3748	1699	2049	3748

Notes: Column 1 shows mean and standard deviations (square bracket) for full sample, while columns 2 and 3 divided into female and male, respectively. Column 4 gives a difference in means and statistical difference of pairwise t-test. The sample is restricted to individuals aged 6-20 in Kenya and 7-17 in Ethiopia years as of the 2020 in Kenya (R7 survey) and 2022 in Ethiopia (R5 survey). Birth order "First born", "Second born", "Third born", and "Fourth or more born" are defined based on the order of age among the sample siblings. The data on child time use is available only for Ethiopia ($N = 948$). * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A3: Effects of productivity shocks on livestock loss

	Livestock lost due to droughts (CMVE)		Livetock lost (CMVE)	
	(1)	(2)	(3)	(4)
Positive productivity shock	0.136	0.228	-0.898***	-1.129**
	(0.311)	(0.428)	(0.310)	(0.484)
Negative productivity shock	-0.851***	-1.897***	3.384***	3.786***
	(0.184)	(0.432)	(0.773)	(0.912)
Household fixed effects		✓		✓
Adjusted R-squared	0.002	-0.031	0.031	0.119
Observations	1365	1365	7836	7836

Notes: The table shows the association between livestock losses and productivity shocks in the year of survey. The data is from household panel data set in 2009, 2010, 2011, 2012, 2013, 2015, 2020, in Kenya and 2012, 2013, 2014, 2015, 2022, in Ethiopia. The outcomes are "livestock lost due to droughts", "livestock lost", and "distress sales". Productivity shocks are censored z-score NDVI in absolute value in the year of survey. Standard errors are clustered at the community level. The row "Household fixed effects" indicates whether to control for the household fixed effects. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. In Kenya, 1 CMVE= 0.625 camel=1 cattle=10 goats/sheep, and in Ethiopia, 1 CMVE=0.4 camel=1 cattle=6.25 goats/sheep.

Table A4: Summary statistics of worst/best shocks at binned-age

	Mean/SD	Min	Max
Postive productivity shocks			
Infants (0-2)	0.41	0.00	8.97
	[0.86]		
Preschoolers (3-5)	0.50	0.00	8.96
	[0.95]		
Early primary (6-8)	0.81	0.00	8.96
	[1.19]		
Mid primary (9-11)	0.65	0.00	6.99
	[1.08]		
Late primary (12-14)	0.58	0.00	8.96
	[1.06]		
Negative productivity shocks			
Infants (0-2)	0.44	0.00	2.53
	[0.57]		
Preschoolers (3-5)	0.44	0.00	2.53
	[0.57]		
Early primary (6-8)	0.40	0.00	2.53
	[0.61]		
Mid primary (9-11)	0.36	0.00	2.53
	[0.61]		
Late primary (12-14)	0.24	0.00	2.48
	[0.55]		
Observations	3748		

Notes: The sample is restricted to individuals aged older than 7 and younger than 20 as of the 2020 (R7) survey. Positive productivity shocks are defined as the cumulative sum of censored NDVI z-scores within each age bin, buffered within 5 km of each household's location. Negative productivity shocks are defined as the maximum absolute value of the censored NDVI z-score within each age bin, buffered within 15 km of each household's location.

Table A5: Effects of cumulative positive productivity shocks at different stages of childhood

	Completed years of education at endline			
	(1)	(2)	(3)	(4)
Postive productivity shocks				
Infants (0-2)	0.060	0.069	0.057	-0.052
	(0.115)	(0.124)	(0.113)	(0.107)
Preschoolers (3-5)	0.251*	0.253**	0.266**	0.149**
	(0.123)	(0.122)	(0.120)	(0.064)
Early primary (6-8)	0.102	0.132	0.109	0.021
	(0.124)	(0.135)	(0.121)	(0.069)
Mid primary (9-11)	0.080	0.091	0.046	-0.028
	(0.096)	(0.106)	(0.070)	(0.055)
Late primary (12-14)	-0.010	0.003	0.045	-0.113
	(0.124)	(0.129)	(0.089)	(0.087)
Controls	✓		✓	✓
Birth-year fixed effects	✓	✓		✓
Household fixed effects	✓	✓	✓	
Community fixed effects				✓
F-statistic for positive shocks	1.185	1.161	2.202	2.303
P-value for F-test for positive shocks	0.339	0.350	0.079	0.069
Observations	3748	3748	3748	3748

Notes: The table presents estimated effects of the cumulative censored z-score NDVI, buffered around 5km for each household location, respectively, at different age bins during childhood, up to age 14, on educational attainment. The dependent variable, "Completed years of education", is measured at the time of the endline survey in Kenya (2020) and Ethiopia (2022). Column (1) reports the preferred specification in equation 3, including cohort fixed effects, household fixed effects, and control variables. Column (2) omits the control variables. Column (3) drops birth-year fixed effects. Column (4) replaces household fixed effects with community fixed effects. All columns use the full sample. The productivity shocks in each binned age are defined as the sum of the z-score NDVI for negative and positive productivity shocks. The binned age correspond to the following age groups: "Infants" (age 0-2), "Preschoolers" (age 3-5), "Early primary" (age 6-8), "Mid primary" (age 9-11), and "Late primary" (age 12-14). Control variables include gender, age, birth order dummies for each child, the number of school-aged children, and TLU class in the baseline household survey. Birth-year fixed effects control for age-specific dummies, and household fixed effects are dummies for each household. The rows "F-statistic for negative/positive shocks" and "*P*-value for negative/positive shocks" present the joint test of whether the coefficients for negative or positive shocks are zero, with *P*-values reported. Standard errors are clustered at the community level. The full sample data includes individuals aged 6-20 in Kenya and children aged 7-17 at the time of the endline survey in Ethiopia. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A6: Effects of the worst productivity shocks at different stages of childhood

	Completed years of education at endline			
	(1)	(2)	(3)	(4)
Negative productivity shocks				
Infants (0-2)	0.093	0.105	-0.002	0.091
	(0.135)	(0.147)	(0.146)	(0.112)
Preschoolers (3-5)	0.273	0.283	0.286	0.221
	(0.208)	(0.222)	(0.221)	(0.139)
Early primary (6-8)	0.222	0.235	0.229	0.178
	(0.139)	(0.152)	(0.144)	(0.120)
Mid primary (9-11)	0.305^{**}	0.301^{**}	0.234^{*}	0.191
	(0.124)	(0.122)	(0.120)	(0.119)
Late primary (12-14)	0.239	0.260	0.284^{*}	0.086
	(0.164)	(0.168)	(0.144)	(0.155)
Controls	✓		✓	✓
Birth-year fixed effects	✓	✓		✓
Household fixed effects	✓	✓	✓	
Community fixed effects				✓
F-statistic for negative shocks	2.062	2.199	1.598	1.857
P-value for F-test for negative shocks	0.097	0.080	0.190	0.131
Observations	3748	3748	3748	3748

Notes: The table presents estimated effects of the worst censored z-score NDVI, buffered around 15km for each household location, respectively, at different age bins during childhood, up to age 14, on educational attainment. The dependent variable, "Completed years of education", is measured at the time of the endline survey in Kenya (2020) and Ethiopia (2022). Column (1) reports the preferred specification in equation 3, including cohort fixed effects, household fixed effects, and control variables. Column (2) omits the control variables. Column (3) drops birth-year fixed effects. Column (4) replaces household fixed effects with community fixed effects. All columns use the full sample. The productivity shocks in each binned age are defined as the sum of the z-score NDVI for negative and positive productivity shocks. The binned age correspond to the following age groups: "Infants" (age 0-2), "Preschoolers" (age 3-5), "Early primary" (age 6-8), "Mid primary" (age 9-11), and "Late primary" (age 12-14). Control variables include gender, age, birth order dummies for each child, the number of school-aged children, and TLU class in the baseline household survey. Birth-year fixed effects control for age-specific dummies, and household fixed effects are dummies for each household. The rows "F-statistic for negative/positive shocks" and "*P*-value for negative/positive shocks" present the joint test of whether the coefficients for negative or positive shocks are zero, with *P*-values reported. Standard errors are clustered at the community level. The full sample data includes individuals aged 6-20 in Kenya and children aged 7-17 at the time of the endline survey in Ethiopia. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A7: Effects of best productivity shocks at different stages of childhood

	Completed years of education at endline			
	(1)	(2)	(3)	(4)
Postive productivity shocks				
Infants (0-2 yrs. old)	0.065	0.078	0.045	-0.123
	(0.137)	(0.146)	(0.136)	(0.139)
Preschoolers (3-5 yrs. old)	0.223	0.213	0.239*	0.185*
	(0.135)	(0.127)	(0.136)	(0.095)
Early primary school (6-8 yrs. old)	0.163	0.179	0.149	0.097
	(0.161)	(0.169)	(0.151)	(0.087)
Mid-primary school (9-11 yrs. old)	0.132	0.120	0.052	0.007
	(0.093)	(0.095)	(0.073)	(0.076)
Late primary school (12-14 yrs. old)	0.077	0.082	0.094	-0.038
	(0.157)	(0.161)	(0.113)	(0.116)
Controls	✓		✓	✓
Birth-year fixed effects	✓	✓		✓
Household fixed effects	✓	✓	✓	
Community fixed effects				✓
F-statistic for positive shocks	0.765	0.782	1.005	1.805
P-value for F-test for positive shocks	0.582	0.570	0.431	0.141
Observations	3748	3748	3748	3748

Notes: The table presents estimated effects of the censored z-score NDVI at different age bins during childhood, up to age 14, on educational attainment. The dependent variable, "Completed years of education", is measured at the time of the endline survey in Kenya (2020) and Ethiopia (2022). Column 1 uses the all the samples while Columns 2-5 restrict the sample children those whose age is equal to or above the age at shocks. For example, Column 3 restricts the samples those who are equal to or above age 8, and look at the effects of productivity shocks up to age 8. The productivity shocks in each binned age are defined as the sum of the z-score NDVI for negative and positive productivity shocks. The binned age correspond to the following age groups: "Infants" (age 0-2), "Preschoolers" (age 3-5), "Early primary" (age 6-8), "Mid primary" (age 9-11), and "Late primary" (age 12-14). Control variables include gender, age, birth order dummies for each child, the number of school-aged children, and TLU class in the baseline household survey. Birth-year fixed effects control for age-specific dummies, and household fixed effects are dummies for each household. The rows "F-statistic for negative/positive shocks" and "*P*-value for negative/positive shocks" present the joint test of whether the coefficients for negative or positive shocks are zero, with *P*-values reported. Standard errors are clustered at the community level. The full sample data includes individuals aged 6-20 in Kenya and children aged 7-17 at the time of the endline survey in Ethiopia. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A8: Effects of cumulative productivity shocks at different stages of childhood

	Completed years of education at endline			
	(1)	(2)	(3)	(4)
Negative productivity shocks				
Infants (0-2)	0.139	0.163	0.083	0.073
	(0.130)	(0.141)	(0.130)	(0.079)
Preschoolers (3-5)	0.264	0.294	0.297	0.166
	(0.200)	(0.214)	(0.194)	(0.111)
Early primary (6-8)	0.211	0.236	0.226	0.131
	(0.179)	(0.194)	(0.172)	(0.125)
Mid primary (9-11)	0.214	0.221	0.196	0.076
	(0.161)	(0.175)	(0.149)	(0.122)
Late primary (12-14)	0.147	0.164	0.224*	-0.030
	(0.141)	(0.144)	(0.125)	(0.135)
Controls	✓		✓	✓
Birth-year fixed effects	✓	✓		✓
Household fixed effects	✓	✓	✓	
Community fixed effects				✓
F-statistic for negative shocks	0.643	0.778	1.321	0.629
P-value for F-test for negative shocks	0.669	0.573	0.281	0.679
Observations	3748	3748	3748	3748

Notes: The table presents estimated effects of the censored z-score NDVI at different age bins during childhood, up to age 14, on educational attainment. The dependent variable, "Completed years of education", is measured at the time of the endline survey in Kenya (2020) and Ethiopia (2022). Column 1 uses the all the samples while Columns 2-5 restrict the sample children those whose age is equal to or above the age at shocks. For example, Column 3 restricts the samples those who are equal to or above age 8, and look at the effects of productivity shocks up to age 8. The productivity shocks in each binned age are defined as the sum of the z-score NDVI for negative and positive productivity shocks. The binned age correspond to the following age groups: "Infants" (age 0-2), "Preschoolers" (age 3-5), "Early primary" (age 6-8), "Mid primary" (age 9-11), and "Late primary" (age 12-14). Control variables include gender, age, birth order dummies for each child, the number of school-aged children, and TLU class in the baseline household survey. Birth-year fixed effects control for age-specific dummies, and household fixed effects are dummies for each household. The rows "F-statistic for negative/positive shocks" and "*P*-value for negative/positive shocks" present the joint test of whether the coefficients for negative or positive shocks are zero, with *P*-values reported. Standard errors are clustered at the community level. The full sample data includes individuals aged 6-20 in Kenya and children aged 7-17 at the time of the endline survey in Ethiopia. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A9: Effects of cumulative positive productivity shocks with samples older than time of the shocks

	Outcome: Completed years of education at endline									
	Full sample		Samples older than time of the shocks							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Postive productivity shocks										
Infants (0-2)	0.060	-0.052	0.026	-0.059	0.075	-0.042	0.084	0.019	-0.218	-0.118
	(0.115)	(0.107)	(0.106)	(0.097)	(0.128)	(0.116)	(0.204)	(0.155)	(0.342)	(0.172)
Preschoolers (3-5)	0.251*	0.149**	0.217**	0.148**	0.297***	0.172**	0.334*	0.189**	0.059	0.434***
	(0.123)	(0.064)	(0.093)	(0.062)	(0.094)	(0.068)	(0.167)	(0.090)	(0.509)	(0.144)
Early primary (6-8)	0.102	0.021			0.046	0.006	0.062	-0.067	0.154	0.050
	(0.124)	(0.069)			(0.104)	(0.065)	(0.192)	(0.092)	(0.376)	(0.124)
Mid primary (9-11)	0.080	-0.028					0.108	-0.031	-0.037	-0.188
	(0.096)	(0.055)					(0.159)	(0.082)	(0.492)	(0.154)
Late primary (12-14)	-0.010	-0.113							-0.168	-0.146
	(0.124)	(0.087)							(0.476)	(0.094)
Negative shocks	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Birth-year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Household fixed effects	✓		✓		✓		✓		✓	
F-statistic for positive shocks	1.185	2.303	2.869	3.989	3.630	4.126	1.769	2.574	0.219	3.203
P-value for F-test for positive shocks	0.339	0.069	0.072	0.029	0.024	0.014	0.160	0.057	0.952	0.019
Observations	3748	3748	3748	3748	3279	3279	2281	2281	1377	1377

Notes: The table presents estimated effects of the cumulative censored z-score NDVI, buffered around 5km for each household location, respectively, at different age bins during childhood, up to age 14, on educational attainment. The dependent variable, "Completed years of education", is measured at the time of the endline survey in Kenya (2020) and Ethiopia (2022). Columns 1-2 use the all the samples while Columns 3-10 restrict the sample children whose age is equal to or above the age at shocks. For example, Column 5 restricts the samples those who are equal to or above age 8, and look at the effects of productivity shocks up to age 8. The productivity shocks in each binned age are defined as the sum of the z-score NDVI for negative and positive productivity shocks during each binned ages. The binned age correspond to the following age groups: "Infants" (age 0-2), "Preschoolers" (age 3-5), "Early primary" (age 6-8), "Mid primary" (age 9-11), and "Late primary" (age 12-14). Control variables include gender, age, birth order dummies for each child, the number of school-aged children, and TLU class in the baseline household survey. Birth-year fixed effects control for age-specific dummies, and household fixed effects are dummies for each household. The rows "F-statistic for negative/positive shocks" and "*P*-value for positive shocks" present the joint test of whether the coefficients for negative or positive shocks are zero, with *P*-values reported. Standard errors are clustered at the community level. The full sample data includes individuals aged 6-20 in Kenya and children aged 7-17 at the time of the endline survey in Ethiopia. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A10: Effects of the worst productivity shocks at different stages of childhood with samples older than time of the shocks

	Outcome: Completed years of education at endline									
	Full sample		Samples older than time of the shocks							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Negative productivity shocks										
Infants (0-2)	0.093	0.091	0.020	0.062	-0.026	0.063	-0.059	0.138	0.331	0.103
	(0.135)	(0.112)	(0.148)	(0.110)	(0.170)	(0.123)	(0.338)	(0.205)	(0.442)	(0.299)
Preschoolers (3-5)	0.273	0.221	0.173	0.213	0.106	0.175	0.097	0.174	0.406	0.370
	(0.208)	(0.139)	(0.188)	(0.134)	(0.209)	(0.148)	(0.319)	(0.217)	(0.626)	(0.299)
Early primary (6-8)	0.222	0.178			0.069	0.160	0.069	0.158	0.432	0.184
	(0.139)	(0.120)			(0.156)	(0.118)	(0.287)	(0.214)	(0.502)	(0.245)
Mid primary (9-11)	0.305**	0.191					0.073	0.137	0.490	0.272
	(0.124)	(0.119)					(0.243)	(0.154)	(0.706)	(0.281)
Late primary (12-14)	0.239	0.086							0.260	0.320
	(0.164)	(0.155)							(0.540)	(0.242)
Positive shocks	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Birth-year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Household fixed effects	✓		✓		✓		✓		✓	
F-statistic for negative shocks	2.062	1.857	0.502	1.259	0.142	0.727	0.074	0.838	0.307	1.264
P-value for F-test for negative shocks	0.097	0.131	0.610	0.298	0.934	0.544	0.990	0.512	0.905	0.304
Observations	3748	3748	3748	3748	3279	3279	2281	2281	1377	1377

Notes: The table presents estimated effects of the worst censored z-score NDVI, buffered around 15km for each household location, respectively, at different age bins during childhood, up to age 14, on educational attainment. The dependent variable, "Completed years of education", is measured at the time of the endline survey in Kenya (2020) and Ethiopia (2022). Column 1-2 use the all the samples while Columns 3-10 restrict the sample children whose age is equal to or above the age at shocks. For example, Column 5 restricts the samples those who are equal to or above age 8, and look at the effects of productivity shocks up to age 8. The productivity shocks in each binned age are defined as the maximum of the z-score NDVI for negative and positive productivity shocks during each binned ages. The binned age correspond to the following age groups: "Infants" (age 0-2), "Preschoolers" (age 3-5), "Early primary" (age 6-8), "Mid primary" (age 9-11), and "Late primary" (age 12-14). Control variables include gender, age, birth order dummies for each child, the number of school-aged children, and TLU class in the baseline household survey. Birth-year fixed effects control for age-specific dummies, and household fixed effects are dummies for each household. The rows "F-statistic for negative shocks" and "*P*-value for negative/positive shocks" present the joint test of whether the coefficients for negative or positive shocks are zero, with *P*-values reported. Standard errors are clustered at the community level. The full sample data includes individuals aged 6-20 in Kenya and children aged 7-17 at the time of the endline survey in Ethiopia. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A11: Effects of cumulative productivity shocks by different buffer sizes

	Outcome: Completed years of education at endline			
	5km	10km	15km	20km
	(1)	(2)	(3)	(4)
Positive productivity shocks				
Infants (0-2)	0.060	-0.021	-0.138	-0.131
	(0.115)	(0.096)	(0.127)	(0.155)
Preschoolers (3-5)	0.251*	0.168	0.090	0.128
	(0.123)	(0.132)	(0.147)	(0.164)
Early primary (6-8)	0.102	0.136	0.090	0.098
	(0.124)	(0.117)	(0.133)	(0.159)
Mid primary (9-11)	0.080	0.150	0.055	0.089
	(0.096)	(0.112)	(0.132)	(0.142)
Late primary (12-14)	-0.010	0.016	-0.070	-0.086
	(0.124)	(0.128)	(0.126)	(0.126)
Controls	✓	✓	✓	✓
Birth-year fixed effects	✓	✓	✓	✓
Household fixed effects	✓	✓	✓	✓
F-statistic for negative shocks	0.675	0.580	0.643	0.703
P-value for F-test for negative shocks	0.646	0.715	0.669	0.625
Observations	3748	3748	3748	3748

Notes: The table presents estimated effects of the censored z-score NDVI at different age bins during childhood, up to age 14, on educational attainment. The dependent variable, "Completed years of education", is measured at the time of the endline survey in Kenya (2020) and Ethiopia (2022). All columns use the same specification but with different buffer sizes for the shock variables: 5km, 10km, 15km, and 20km, in that order. The productivity shocks in each binned age are defined as the sum of the z-score NDVI for negative and positive productivity shocks. The binned age correspond to the following age groups: "Infants" (age 0-2), "Preschoolers" (age 3-5), "Early primary" (age 6-8), "Mid primary" (age 9-11), and "Late primary" (age 12-14). Control variables include gender, age, birth order dummies for each child, the number of school-aged children, and TLU class in the baseline household survey. Birth-year fixed effects control for age-specific dummies, and household fixed effects are dummies for each household. The rows "F-statistic for negative/positive shocks" and "*P*-value for negative/positive shocks" present the joint test of whether the coefficients for negative or positive shocks are zero, with *P*-values reported. Standard errors are clustered at the community level. The full sample data includes individuals aged 6-20 in Kenya and children aged 7-17 at the time of the endline survey in Ethiopia. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A12: Effects of worst productivity shocks by different buffer sizes

	Outcome: Completed years of education at endline			
	5km	10km	15km	20km
	(1)	(2)	(3)	(4)
Negative productivity shocks				
Infants (0-2)	0.080	0.174	0.093	0.008
	(0.170)	(0.156)	(0.135)	(0.139)
Preschoolers (3-5)	0.314	0.269	0.273	0.299**
	(0.206)	(0.202)	(0.208)	(0.136)
Early primary (6-8)	0.174	0.168	0.222	0.167
	(0.174)	(0.163)	(0.139)	(0.130)
Mid primary (9-11)	0.129	0.201	0.305**	0.316*
	(0.134)	(0.155)	(0.124)	(0.158)
Late primary (12-14)	0.183	0.199	0.239	0.247
	(0.178)	(0.163)	(0.164)	(0.156)
Controls	✓	✓	✓	✓
Birth-year fixed effects	✓	✓	✓	✓
Household fixed effects	✓	✓	✓	✓
F-statistic for negative shocks	0.751	0.797	2.062	2.242
P-value for F-test for negative shocks	0.591	0.560	0.097	0.075
Observations	3748	3748	3748	3748

Notes: The table presents estimated effects of the censored z-score NDVI at different age bins during childhood, up to age 14, on educational attainment. The dependent variable, "Completed years of education", is measured at the time of the endline survey in Kenya (2020) and Ethiopia (2022). All columns use the same specification but with different buffer sizes for the shock variables: 5km, 10km, 15km, and 20km, in that order. The productivity shocks in each binned age are defined as the sum of the z-score NDVI for negative and positive productivity shocks. The binned age correspond to the following age groups: "Infants" (age 0-2), "Preschoolers" (age 3-5), "Early primary" (age 6-8), "Mid primary" (age 9-11), and "Late primary" (age 12-14). Control variables include gender, age, birth order dummies for each child, the number of school-aged children, and TLU class in the baseline household survey. Birth-year fixed effects control for age-specific dummies, and household fixed effects are dummies for each household. The rows "F-statistic for negative/positive shocks" and "*P*-value for negative/positive shocks" present the joint test of whether the coefficients for negative or positive shocks are zero, with *P*-values reported. Standard errors are clustered at the community level. The full sample data includes individuals aged 6-20 in Kenya and children aged 7-17 at the time of the endline survey in Ethiopia. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A13: Effects of the negative productivity shocks on child time use at different stages of childhood

	Herding labor (=1)	Housework (=1)	Any schooling (=1)
	(1)	(2)	(3)
Reference category: age 6-8			
Lagged negative shock	0.005	-0.030	0.031
	(0.022)	(0.024)	(0.025)
Binned age=9-11 × Lagged negative shock	-0.029	0.003	0.015
	(0.028)	(0.025)	(0.029)
Binned age=12-14 × Lagged negative shock	-0.065***	-0.000	0.044
	(0.023)	(0.030)	(0.028)
Current negative shock	-0.045**	0.055**	-0.009
	(0.019)	(0.022)	(0.020)
Binned age=9-11 × Current negative shock	-0.018	-0.006	0.040*
	(0.017)	(0.018)	(0.023)
Binned age=12-14 × Current negative shock	-0.027*	-0.021	0.057**
	(0.015)	(0.017)	(0.021)
Controls	✓	✓	✓
Community fixed effects	✓	✓	✓
Round fixed effects	✓	✓	✓
Lagged coef. for age 9-11	-0.025	-0.027	0.045
p-value for age 9-11	0.328	0.398	0.054
Lagged coef. for age 12-14	-0.060	-0.031	0.075
p-value for age 12-14	0.001	0.355	0.000
Current coef. for age 9-11	-0.062	0.048	0.031
p-value for age 9-11	0.006	0.025	0.067
Current coef. for age 12-14	-0.072	0.033	0.048
p-value for age 12-14	0.001	0.074	0.007
Observations	18587	18587	18587

Notes: This table presents the effects of productivity shocks at different time points–both in the lagged year and the current year–on children's time use. Time use is measured at each wave of the panel household survey conducted since 2009 in Kenya and Ethiopia. The outcome variables are binary indicators for whether a child works with livestock, performs housework, or attends school. The reference category for both lagged and current negative shocks consists of children aged 6–8. Control variables include gender, age, birth order dummies for each child, the number of school-aged children, and livestock holdings in CMVE. Corresponding positive shocks and community fixed effects. The rows "coef." and "*p*-value" for each shock for different age bins present th test for each estimates. Standard errors are clustered at the community level. The sample includes individuals aged 6-20 in Kenya and children aged 7-17. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A14: Effects of the negative productivity shocks on child time use at different stages of childhood with household fixed effect

	Herding labor (=1)	Housework (=1)	Any schooling (=1)
	(1)	(2)	(3)
Reference category: age 6-8			
Lagged negative shock	0.014	-0.038	0.025
	(0.025)	(0.028)	(0.023)
Binned age=9-11 × Lagged negative shock	-0.028	0.013	0.003
	(0.027)	(0.027)	(0.027)
Binned age=12-14 × Lagged negative shock	-0.071***	0.007	0.049
	(0.024)	(0.031)	(0.029)
Current negative shock	-0.035	0.058**	-0.017
	(0.022)	(0.024)	(0.021)
Binned age=9-11 × Current negative shock	-0.027*	-0.006	0.042*
	(0.016)	(0.018)	(0.023)
Binned age=12-14 × Current negative shock	-0.025	-0.022	0.059**
	(0.017)	(0.018)	(0.022)
Controls	✓	✓	✓
Household fixed effects	✓	✓	✓
Round fixed effects	✓	✓	✓
Lagged coef. for age 9-11	-0.014	-0.025	0.027
p-value for age 9-11	0.584	0.474	0.145
Lagged coef. for age 12-14	-0.057	-0.031	0.073
p-value for age 12-14	0.005	0.391	0.000
Current coef. for age 9-11	-0.062	0.052	0.025
p-value for age 9-11	0.013	0.025	0.116
Current coef. for age 12-14	-0.060	0.037	0.042
p-value for age 12-14	0.012	0.057	0.018
Observations	18587	18587	18587

Notes: This table presents the effects of productivity shocks at different time points–both in the lagged year and the current year–on children's time use. Time use is measured at each wave of the panel household survey conducted since 2009 in Kenya and Ethiopia. The outcome variables are binary indicators for whether a child works with livestock, performs housework, or attends school. The reference category for both lagged and current negative shocks consists of children aged 6–8. Control variables include gender, age, birth order dummies for each child, the number of school-aged children, and livestock holdings in CMVE. Corresponding positive shocks and household fixed effects. The rows "coef." and "*p*-value" for each shock for different age bins present th test for each estimates. Standard errors are clustered at the community level. The sample includes individuals aged 6-20 in Kenya and children aged 7-17. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A15: Effects of the negative productivity shocks on child time use at different stages of childhood cluster standard errors at household level

	Herding labor (=1)	Housework (=1)	Any schooling (=1)
	(1)	(2)	(3)
Reference category: age 6-8			
Lagged negative shock	0.014	-0.038**	0.025
	(0.016)	(0.019)	(0.017)
Binned age=9-11 × Lagged negative shock	-0.028	0.013	0.003
	(0.022)	(0.023)	(0.022)
Binned age=12-14 × Lagged negative shock	-0.071***	0.007	0.049**
	(0.022)	(0.024)	(0.020)
Current negative shock	-0.035**	0.058***	-0.017
	(0.015)	(0.016)	(0.016)
Binned age=9-11 × Current negative shock	-0.027	-0.006	0.042**
	(0.018)	(0.019)	(0.020)
Binned age=12-14 × Current negative shock	-0.025	-0.022	0.059***
	(0.020)	(0.018)	(0.020)
Controls	✓	✓	✓
Community fixed effects			
Round fixed effects	✓	✓	✓
Lagged coef. for age 9-11	-0.014	-0.025	0.027
p-value for age 9-11	0.453	0.194	0.089
Lagged coef. for age 12-14	-0.057	-0.031	0.073
p-value for age 12-14	0.001	0.106	0.000
Current coef. for age 9-11	-0.062	0.052	0.025
p-value for age 9-11	0.000	0.001	0.070
Current coef. for age 12-14	-0.060	0.037	0.042
p-value for age 12-14	0.000	0.016	0.003
Observations	18587	18587	18587

Notes: This table presents the effects of productivity shocks at different time points–both in the lagged year and the current year–on children's time use. Time use is measured at each wave of the panel household survey conducted since 2009 in Kenya and Ethiopia. The outcome variables are binary indicators for whether a child works with livestock, performs housework, or attends school. The reference category for both lagged and current negative shocks consists of children aged 6–8. Control variables include gender, age, birth order dummies for each child, the number of school-aged children, and livestock holdings in CMVE. Corresponding positive shocks and household fixed effects. The rows "coef." and "*p*-value" for each shock for different age bins present th test for each estimates. Standard errors are clustered at the household level. The sample includes individuals aged 6-20 in Kenya and children aged 7-17. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A16: Effects of the negative productivity shocks on child time use at different stages of childhood for male

	Herding labor (=1)	Any schooling (=1)
	(1)	(2)
Reference category: age 6-8		
Lagged negative shock	-0.037	0.014
	(0.030)	(0.035)
Binned age=9-11 × Lagged negative shock	-0.001	0.038
	(0.037)	(0.039)
Binned age=12-14 × Lagged negative shock	-0.021	0.060
	(0.039)	(0.043)
Current negative shock	-0.058**	0.005
	(0.022)	(0.022)
Binned age=9-11 × Current negative shock	-0.002	0.025
	(0.024)	(0.033)
Binned age=12-14 × Current negative shock	0.005	0.042
	(0.022)	(0.032)
Controls	✓	✓
Community fixed effects	✓	✓
Round fixed effects	✓	✓
Lagged coef. for age 9-11	-0.038	0.053
p-value for age 9-11	0.187	0.026
Lagged coef. for age 12-14	-0.059	0.074
p-value for age 12-14	0.040	0.001
Current coef. for age 9-11	-0.060	0.030
p-value for age 9-11	0.040	0.168
Current coef. for age 12-14	-0.053	0.047
p-value for age 12-14	0.049	0.044
Observations	9887	9887

Notes: This table presents the effects of productivity shocks at different time points–both in the lagged year and the current year–on children's time use for male. Time use is measured at each wave of the panel household survey conducted since 2009 in Kenya and Ethiopia. The outcome variables are binary indicators for whether a child works with livestock, performs housework, or attends school. The reference category for both lagged and current negative shocks consists of children aged 6–8. Control variables include gender, age, birth order dummies for each child, the number of school-aged children, and livestock holdings in CMVE. Corresponding positive shocks and community fixed effects. The rows "coef." and "p-value" for each shock for different age bins present th test for each estimates. Standard errors are clustered at the community level. The sample includes individuals aged 6-20 in Kenya and children aged 7-17. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A17: Effects of the negative productivity shocks on child time use at different stages of childhood for female

	Housework (=1)	Any schooling (=1)
	(1)	(2)
Reference category: age 6-8		
Lagged negative shock	-0.048	0.043*
	(0.031)	(0.022)
Binned age=9-11 × Lagged negative shock	0.009	-0.005
	(0.035)	(0.043)
Binned age=12-14 × Lagged negative shock	0.005	0.034
	(0.038)	(0.030)
Current negative shock	0.079**	-0.023
	(0.034)	(0.026)
Binned age=9-11 × Current negative shock	-0.032	0.056*
	(0.033)	(0.028)
Binned age=12-14 × Current negative shock	-0.041	0.076**
	(0.032)	(0.034)
Controls	✓	✓
Community fixed effects	✓	✓
Round fixed effects	✓	✓
Lagged coef. for age 9-11	-0.040	0.038
p-value for age 9-11	0.312	0.299
Lagged coef. for age 12-14	-0.043	0.077
p-value for age 12-14	0.313	0.002
Current coef. for age 9-11	0.047	0.033
p-value for age 9-11	0.109	0.216
Current coef. for age 12-14	0.038	0.054
p-value for age 12-14	0.168	0.022
Observations	8700	8700

Notes: This table presents the effects of productivity shocks at different time points–both in the lagged year and the current year–on children's time use for male. Time use is measured at each wave of the panel household survey conducted since 2009 in Kenya and Ethiopia. The outcome variables are binary indicators for whether a child works with livestock, performs housework, or attends school. The reference category for both lagged and current negative shocks consists of children aged 6–8. Control variables include gender, age, birth order dummies for each child, the number of school-aged children, and livestock holdings in CMVE. Corresponding positive shocks and community fixed effects. The rows "coef." and "p-value" for each shock for different age bins present th test for each estimates. Standard errors are clustered at the community level. The sample includes individuals aged 6-20 in Kenya and children aged 7-17. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A18: Effects of the positive productivity shocks on child time use at different stages of childhood

	Herding labor (=1)	Housework (=1)	Any schooling (=1)
	(1)	(2)	(3)
Lagged positive shock	-0.010	0.000	-0.005
	(0.022)	(0.021)	(0.019)
Binned age=9-11 × Lagged positive shock	0.031	-0.004	0.010
	(0.023)	(0.027)	(0.020)
Binned age=12-14 × Lagged positive shock	0.052**	0.028	-0.006
	(0.024)	(0.028)	(0.030)
Current positive shock	-0.010	0.030	0.013
	(0.018)	(0.029)	(0.018)
Binned age=9-11 × Current positive shock	0.023	0.000	-0.017
	(0.023)	(0.033)	(0.024)
Binned age=12-14 × Current positive shock	-0.018	0.004	0.010
	(0.025)	(0.034)	(0.029)
Controls	✓	✓	✓
Community fixed effects	✓	✓	✓
Round fixed effects	✓	✓	✓
Lagged coef. for age 9-11	0.021	-0.004	0.005
p-value for age 9-11	0.282	0.854	0.645
Lagged coef. for age 12-14	0.042	0.028	-0.011
p-value for age 12-14	0.088	0.104	0.530
Current coef. for age 9-11	0.013	0.030	-0.004
p-value for age 9-11	0.437	0.188	0.784
Current coef. for age 12-14	-0.028	0.034	0.024
p-value for age 12-14	0.233	0.148	0.253
Observations	18587	18587	18587

Notes: This table presents the effects of productivity shocks at different time points–both in the lagged year and the current year–on children's time use. Time use is measured at each wave of the panel household survey conducted since 2009 in Kenya and Ethiopia. The outcome variables are binary indicators for whether a child works with livestock, performs housework, or attends school. The reference category for both lagged and current negative shocks consists of children aged 6–8. Control variables include gender, age, birth order dummies for each child, the number of school-aged children, and livestock holdings in CMVE. Corresponding positive shocks and community fixed effects. The rows "coef." and "*p*-value" for each shock for different age bins present th test for each estimates. Standard errors are clustered at the household level. The sample includes individuals aged 6-20 in Kenya and children aged 7-17. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A19: Effects of productivity shocks during preschool age

	Completed years of education	Completed any schooling
	(1)	(2)
Postive productivity shocks		
at age 0	0.095	0.034
	(0.171)	(0.023)
at age 1	0.145	0.045
	(0.245)	(0.028)
at age 2	-0.171	0.004
	(0.180)	(0.023)
at age 3	0.243	0.041
	(0.192)	(0.029)
at age 4	0.326	0.030
	(0.230)	(0.029)
at age 5	0.360*	0.050*
	(0.190)	(0.025)
School-age shocks	✓	✓
Controls	✓	✓
Birth-year fixed effects	✓	✓
Household fixed effects	✓	✓
Observations	3748	3748

Notes: The table presents estimated effects of the censored z-score NDVI at different ages during pre-school age (0-5) on educational attainment. The dependent variables, "Completed years of education" and "Completed any schooling" are measured at the time of the endline survey in Kenya (2020) and Ethiopia (2022). The latter is a dummy taking a value one if a child completes any education. The row "School-age shocks" shows whether the regression controls for the positive and negative productivity shocks during school age (6-14). Other control variables include gender, age, birth order dummies for each child, the number of school-aged children, and TLU class in the baseline household survey. Birth-year fixed effects control for age-specific dummies, and household fixed effects are dummies for each household. Standard errors are clustered at the community level. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A20: Effects of current and lagged productivity shocks on income

	Cash earnings (USD)	Milk income (USD)
	(1)	(2)
Panel A: Positive productivity shocks		
Positive shock	8.321	43.086
	(52.741)	(59.885)
Lag positive shock	24.040	60.767
	(35.165)	(52.608)
Observations	7568	7561

Panel B: Negative productivity shocks

	Cash earnings (USD)	Milk income (USD)
	(1)	(2)
Negative shock	-57.821	158.776
	(38.913)	(189.734)
Lag negative shock	72.181*	-122.063
	(36.251)	(100.382)
Observations	7568	7561

Notes: This table shows the relationship between the current and lagged productivity shocks and household income. Shocks are defined as the censored z-score NDVI relative to community historical distribution. The coverage is annual from January 1st to December 31st. The data is from the panel household survey in Kenya and Ethiopia. All columns control for household fixed effects. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A21: Effects of productivity shocks on migration

	Household fully-settled (=1)	
	(1)	(2)
Panel A: Positive productivity shocks		
Positive shock	0.033	0.040
	(0.025)	(0.026)
Lag positive shock		-0.022
		(0.028)
Observations	7001	6878

Panel B: Negative productivity shocks

	Household fully-settled (=1)	
	(1)	(2)
Negative shock	-0.087**	-0.084**
	(0.034)	(0.035)
Lag negative shock		0.090*
		(0.046)
Observations	7001	6878

Notes: This table shows the relationship between the current and lagged productivity shocks and whether household fully-settled or not. Shocks are defined as the censored z-score NDVI relative to community historical distribution. The coverage is annual from January 1st to December 31st. The data is from the panel household survey in Kenya and Ethiopia. All columns control for household fixed effects. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

B Constructing the Shock Variable

This section explains the construction of the negative and positive productivity shock variables. The initial step involves imputing the GPS location for each household. Subsequently, buffers are created around each household. Within these buffers, we calculate the average value of the Normalized Difference Vegetation Index (NDVI) from 2000 to 2022. We then define a shock based on the deviation from the historical distribution at the index unit level. Using the age information of each child, we construct a history of shock experiences for each child in each year of their life.

The first challenge is tracking the location of household information not only historically but also incorporating the mobile nature of the population. We address this by carefully imputing the location for each year and creating a buffer of locations where each household is likely to seasonally migrate within a year.

B.1 Impute Location and NDVI

To accurately track the location of each household over time, the ideal dataset would include at least yearly location information. Given the nature of the survey design, survey households remain in the same location since the baseline survey. Therefore, we first assume that the location during the survey does not change.[38] This assumption is plausible given our design. The balanced panel is constructed for those present in the latest survey, and each household is tracked and surveyed in the same location. We then impute the same location back to 2000.

B.2 Buffer approach with NDVI

Based on the imputed household locations, I calculate the yearly average NDVI within a 20 km buffer around each household, accounting for the mobility of pastoralists who graze livestock over extensive areas to secure adequate forage. This approach aligns with the findings of Liao et al. (2017), which examined spatial rangeland utilization patterns using continuous fine-scale GPS collar data (>200 days) tracking cattle movement in the Borana zone of southern Ethiopia, within our study area. The study categorized household movements into three types: (i) primarily linear movements between the base camp and principal foraging areas, (ii) the use of both base and satellite camps, and (iii) a distributed network of satellite camps. During normal periods,

[38] In cases where household location is available in multiple rounds and they differ from each other, we impute the location information of the latest and closest round.

pastoralists typically remain within 5 km of their household location. However, at times, they temporarily migrate from the base camp to a satellite camp, with maximum distances reaching 25–30 km—though generally staying below 20 km, with relevance decreasing as distance increases. By adopting an annual and buffered approach, this method effectively captures the rangeland usage patterns associated with seasonal trekking.

B.3 Constructing productivity shock variables

Using the calculated yearly average NDVI, I construct the shock variables as a censored NDVI z-score. This score is the number of standard deviations from the insurance index unit area mean, truncated between $[-t,t]$ for some t. The construction proceeds as follows:

z-score of NDVI for household h in index unit j for year y is

$$NDVIz := \frac{NDVI_{hjy} - \overline{NDVI}_j}{\sigma_j} \tag{6}$$

where $\overline{NDVI}_j$ is the historical mean NDVI for index unit area j, and σ_j is the historical standard deviation of NDVI for index unit j.

Define the positive and negative values outside of truncated range as

$$NDVIz^{-}_{hjy} = \begin{cases} NDVIz & \text{if } NDVIz \leq 0 \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

$$NDVIz^{+}_{hjy} = \begin{cases} NDVIz & \text{if } NDVIz > 0 \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

An indicator variable that takes the value of 0 for $NDVIz$ scores within the range [-t,t] is defined as:

$$NDVInorm_{hjy} = \begin{cases} 0 & \text{if } NDVIz \in [-t,t] \\ 1 & \text{otherwise} \end{cases} \tag{9}$$

Combining, the truncated NDVI z-score is

$$\theta^{-}_{hjy} := |NDVI^{-}_{hjy}| * NDVInorm_{hjy} \tag{10}$$

$$\theta^{+}_{hjy} := NDVI^{+}_{hjy} * NDVInorm_{hjy} \tag{11}$$

This measure effectively captures impacts greater than t or less than $-t$ standard deviations, assuming no impact within the $[-t, t]$ interval. This approach allows us to detect more severe shocks that might have a greater impact, while also accommodating asymmetry between good and bad years.

I define shocks for each household in each year by following the steps outlined above. However, two key decisions must be made. First, the relevant buffer size must be determined. GPS-collar data suggest that 20 km is a reasonable maximum buffer, though a smaller distance might provide a better predictive fit (Liao et al., 2017). To explore this, I consider four buffer sizes: 5 km, 10 km, 15 km, and 20 km. Second, the appropriate cutoff for defining shocks versus normal years must be selected. I take a data-driven approach, using livestock lost due to drought as the reference metric, as drought-related losses are central to the shocks analyzed in this paper. Appendix Figure B1 illustrates the relationship between livestock lost in the past 12 months at the time of the survey—measured in CMVE—and the z-score of NDVI across different buffer distances (5 km to 20 km). The survey was typically conducted in October–November in Kenya and March–April in Ethiopia, except for the endline, which took place in August–September in Kenya and January–February in Ethiopia.[39] This relationship remains relatively stable across distances. Based on this, I propose three potential cutoffs: 1/2 standard deviation, 3/4 standard deviation, and 1 standard deviation. I then assess all possible combinations of buffer size and cutoff threshold—12 in total—to determine which best predicts livestock mortality in terms of model fit (R-squared). This results in 12 potential ways to define productivity shocks: four buffer sizes (5 km, 10 km, 15 km, and 20 km) combined with three cutoff thresholds (1/2 sd, 3/4 sd, and 1 sd).

I then compare which definition predicts the livestock mortality best. To do so, I regress number of livestock lost in the past 12 months on these shock variables for each combination, including household fixed effects.

The results indicate that the choice of buffer and cutoff does not significantly affect the outcomes. The coefficients remain relatively stable, and the adjusted R-squared values are consistently in the 0.10-0.12 interval.

It is important to note that migration patterns vary depending on forage scarcity. During drier periods, such as droughts, pastoralists migrate more extensively compared to normal periods, which is typically captured by distances of 15–20 km, as mentioned above. However, in normal periods, migration tends to be shorter, with a median distance of around 5–10 km Liao et al. (2017). Based on this, I use a 15 km buffer for negative shocks and a 5 km buffer for positive shocks, as this approach is expected to be more precise and less noisy where I have the highest predictive power.

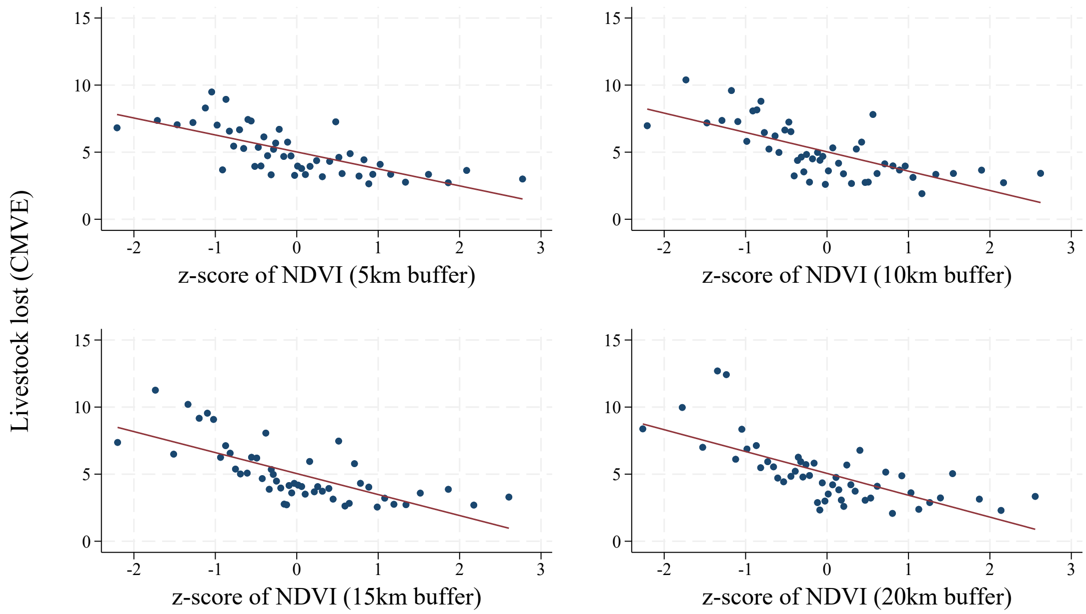
[39] See Barrett et al. (2025) for a more detailed timeline.

Table B1: Livestock lost and productivity shocks defined by different buffer and cutoffs

	Livestock lost in the last 12 months (CMVE)												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
5km													
Positive .5 SD	-1.358***												-1.196**
	(0.467)												(0.436)
Negative .5 SD	3.015***												
	(0.848)												
Positive .75 SD		-1.459***											
		(0.473)											
Negative .75 SD		2.747***											
		(0.802)											
Positive 1 SD			-1.350***										
			(0.461)										
Negative 1 SD			2.527***										
			(0.735)										
10km													
Positive .5 SD				-1.242**									
				(0.467)									
Negative .5 SD				3.741***									
				(0.935)									
Positive .75 SD					-1.258**								
					(0.462)								
Negative .75 SD					3.784***								
					(0.938)								
Positive 1 SD						-1.332***							
						(0.417)							
Negative 1 SD						2.937***							
						(0.831)							
15km													
Positive .5 SD							-1.129**						
							(0.484)						
Negative .5 SD							3.786***						3.777***
							(0.912)						(0.885)
Positive .75 SD								-1.231**					
								(0.478)					
Negative .75 SD								3.781***					
								(0.920)					
Positive 1 SD									-1.292***				
									(0.428)				
Negative 1 SD									3.446***				
									(0.875)				
20km													
Positive .5 SD										-1.026*			
										(0.504)			
Negative .5 SD										3.683***			
										(0.928)			
Positive .75 SD											-1.148**		
											(0.498)		
Negative .75 SD											3.684***		
											(0.940)		
Positive 1 SD												-1.267***	
												(0.444)	
Negative 1 SD												3.533***	
												(0.822)	
Adjusted R-squared	0.105	0.101	0.095	0.116	0.115	0.100	0.119	0.118	0.109	0.119	0.118	0.113	0.119
Observations	7836	7836	7836	7836	7836	7836	7836	7836	7836	7836	7836	7836	7836

Notes: The table shows the association between livestock losses and productivity shocks in the year of survey. The data is from household panel data set in 2009, 2010, 2011, 2012, 2013, 2015, 2020, in Kenya and 2012, 2013, 2014, 2015, 2022, in Ethiopia. The outcomes are "livestock lost in the past 12 months" measured by CMVE. Productivity shocks are censored z-score NDVI in absolute value for each definition: buffered around 5km, 10km, 15km, and 20km for each household location, and the cutoffs at .5SD, .75SD, and 1SD of historical distribution at the community. Standard errors are clustered at the community level. All columns include household fixed effects. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. In Kenya, 1 CMVE= 0.625 camel=1 cattle=10 goats/sheep, and in Ethiopia, 1 CMVE=0.4 camel=1 cattle=6.25 goats/sheep.

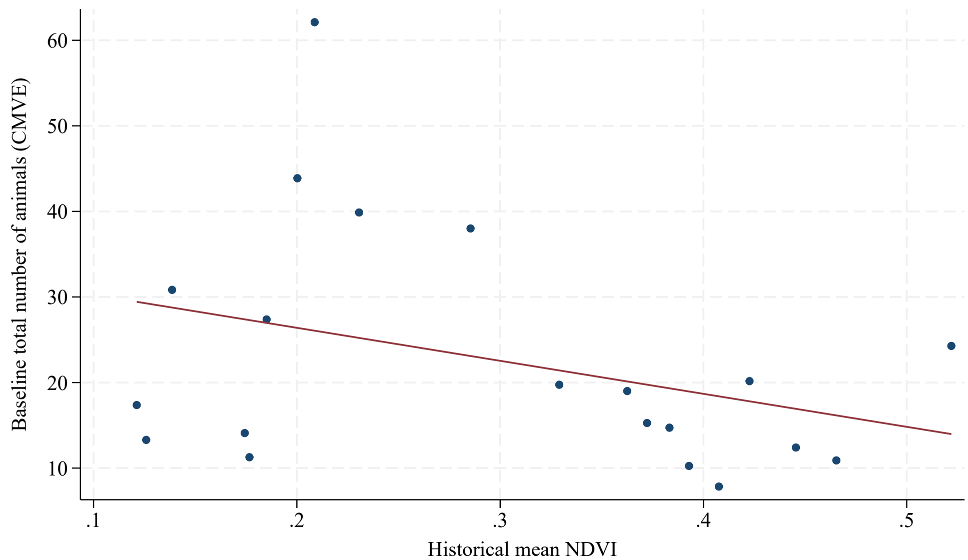
Figure B1: Livestock lost and z-score NDVI with a different buffer size



Notes: This figure shows the relationship between livestock lost (CMVE) and z-score of NDVI. Cattle market-value equivalent (CMVE) is a unit used to aggregate animals across different types based on their market values. In Kenya, 1 CMVE equals 0.625 camels, 1 cattle, or 10 goats/sheep; in Ethiopia, 1 CMVE equals 4 camels, 1 cattle, or 6.25 goats/sheep.

I prefer the censored asymmetric z-score over other potential approaches to define shocks for the following reasons. First, it allows more severe shocks to have larger impacts, effectively isolating severe shocks from moderate ones. Second, it allows asymmetry between negative and positive shocks to have different effects. Third, this method is likely robust to endogenous livestock choice as it is defined as a deviation from the community's historical distribution of NDVI. Indeed, I observe that the location seems to be relevant to livestock production choice. Appendix Figure B2 and Appendix Figure B3 show livestock size and species based on historical mean NDVI. On average, higher historical NDVI places seems to have lower animals. The species composition also varies with range land health conditions.There is a clear positive associations between share of cattle and historical mean NDVI, while the herd share in other species, especially camel, fall as NDVI increases. This seems consistent with the fact that camels are relatively more tolerant to droughts. I particularly prefer this approach over defining shocks as the 20th percentile of the historical distribution at the village level, as used in Jayachandran (2006), Kaur (2019), and Shah and Steinberg (2017). In this setting, I only have 20 years of NDVI data, which may be too short a time series to reliably identify extreme deviations from people's expectations. Furthermore, this approach, by definition, imposes a constant number of shocks on each household, which seems inappropriate in this context.

Figure B2: Baseline total number of animals over historical mean NDVI



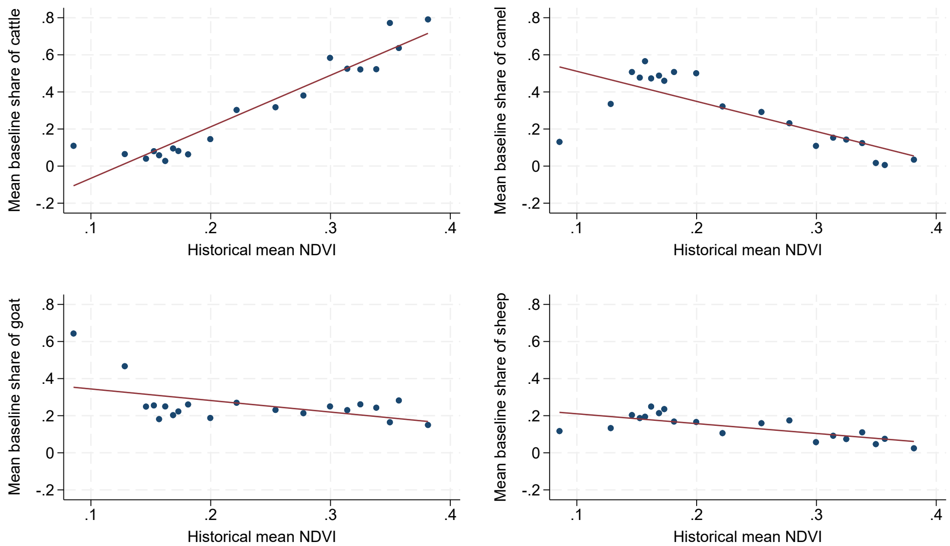
Notes: This figure shows the relationship between total number of animals in 2009 and historical mean of NDVI. Cattle market-value equivalent (CMVE) is a unit used to aggregate animals across different types based on their market values, utilizing panel survey data. In Kenya, 1 CMVE equals 0.625 camels, 1 cattle, or 10 goats/sheep; in Ethiopia, 1 CMVE equals 4 camels, 1 cattle, or 6.25 goats/sheep.

This analysis is likely to be imprecise and not straightforward. First, livestock holdings represent a stock variable rather than a flow, so to assess the effects more precisely, I focus on changes in livestock size rather than the current level. Second, the survey timing occurs a few months after drought periods, meaning the observed livestock size may be influenced by various factors, including household coping mechanisms. Third, outliers are a concern, particularly among households with large livestock holdings, where misreporting may significantly affect the coefficient estimates.

Given these limitations, I estimate the effects of productivity shocks in the current and lagged year on changes in total livestock size, as well as relative changes, defined as the difference divided by the lagged size. The results are presented in Appendix Table **??**. Columns 1 and 2 use the full sample, while column 3 focuses on the lowest 67% of observations based on baseline herd size distribution. This subset is likely more robust to outliers, as larger herders often employ different investment strategies.

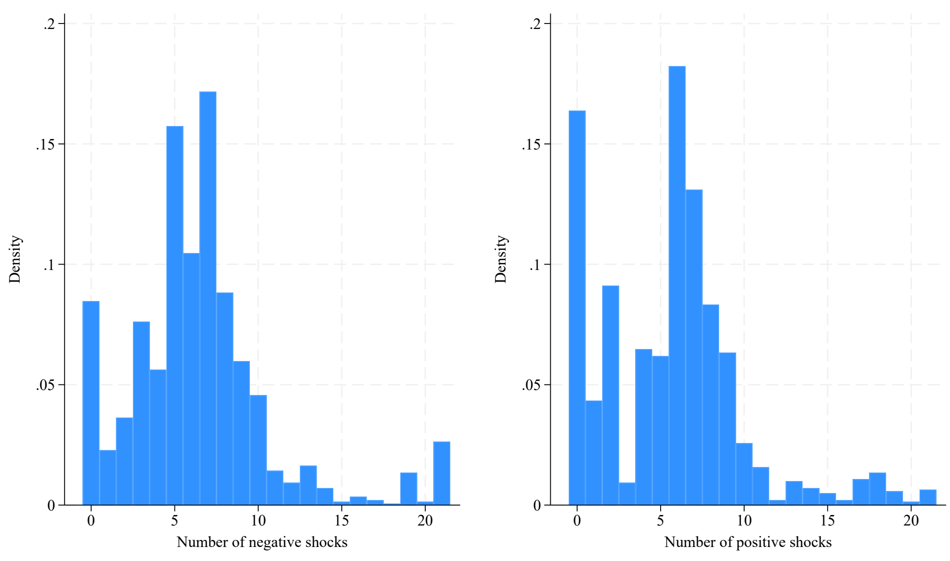
Although imprecisely estimated, column 2 shows that positive shocks are associated with increases in livestock holdings, while negative shocks correspond to decreases. In column 3, the

Figure B3: Share of livestock species over historical mean NDVI



Notes: This figure shows the relationship between share of animal species in 2009 and historical mean of NDVI.

Figure B4: Number of shocks affected



Notes: The sample is restricted to the households who were at endline survey.

coefficients are statistically significant and align with the expected signs. This analysis supports the relevance of income effects—specifically in the context of livestock herding—and the demand for child labor, which is likely influenced by livestock size, in explaining the patterns observed in my main results.

C Attrition analysis

This section discusses the attrition analysis. As the main analysis focuses on cross-sectional data at endline, there is a concern that this sample is biased in selection. Utilizing the panel structure of the data with baseline observations allows for testing whether attrition is endogenous. The sample includes 3,748 children at endline.

At the household level, the research team was able to track 82 percent of the baseline households (1179 out of 1439). households that are female-headed, that have fewer adults, and that do not own agricultural land were more likely to attrit from the sample (See Barrett et al. (2025) for the details).

Since the analysis in this paper focuses on individual level outcomes, the sample selection can happen in two ways: move-out and move-in. The former is those who were at baseline but not in endline, while the latter is those who were not in the baseline but in the endline. This section checks the robustness of the main results and the sample characteristics at endline.

Based on the baseline data (2009 in Kenya and 2011 in Ethiopia), where I focus on children who appear in the endline and who should also be in the baseline sample, the attrition rate is approximately 22.8%.[40] More specifically, among 1,774 children who were in the relevant age group at baseline, I was able to match 1,370 children at endline.

We first verify if we have differential attrition across discount coupon assignment. Because our is the number of seasons that a household received a coupon during the first three sales seasons, we test for differential attrition by estimating equation (12):

$$\text{Attrition}_{ihjT} = \delta_1 \text{D}_{ihj} + \gamma_j + \omega_{ihjt} \tag{12}$$

where $Attrition_{ihjT}$ is an indicator that equals 1 if a household i in household h in location j was interviewed at baseline (2009 in Kenya, 2012 in Ethiopia), but not during the long-run follow-up survey round (2020 in Kenya and 2022 in Ethiopia). D_{ihj} is cumulative z-score NDVI during the study periods. γ_j represents community fixed effects, and ω_{ihjt} the error term, clustered at the community-level. Column (1) of Table C3 reports the results, and we do not find significant differential attrition by the cumulative measure of the productivity shocks during the study periods.

To consider selective attrition by the observable child characteristics, I regress each child char-

[40] The household panel dataset is not an individual-level panel. Therefore, I match individuals across the baseline and endline surveys using household ID, as well as the child's age and gender, allowing for a measurement error of up to three years. This implies that the reported attrition rate is likely a lower bound.

acteristic on the attrition indicator:

$$X_{ihj0} = \xi_1 Attrition_{ihjT} + \sigma^1_{ijt} \tag{13}$$

where X_{ihj0} is the vector of characteristics of a child i in household i in community j at baseline. In addition to each coefficient, we also conduct joint significance tests to verify if all characteristics combined are jointly statistically significantly different. Table C1 shows that older and female children were more likely to attrit from the endline sample.

I then also test selective attrition by regressing the attrition indicator on the vector of child characteristics. I estimate the following equation:

$$Attrition_{ihjT} = \lambda_1 X_{ihj0} + \rho^2_h + \sigma^2_{ihjt} \tag{14}$$

where all variables are defined following Equation 13 except for ρ^2_h which is a household fixed effect. The results reported in Table C2 show that male significantly decreases the likelihood of attrition by 7.2 to 9.3 percentage point. Also, an additional age of a child increases the likelihood of attrition by 3.2-3.9 percentage point, at the 1 percent level.

Table C1: Attrition by child baseline characteristics

	Independent variable: Interviewed at baseline but not in the final round (=1)
	(1)
Age	1.78***
	(.315)
Male (=1)	-.107**
	(.0545)
First born (=1)	.0876**
	(.0371)
Second born (=1)	.0598
	(.0405)
Third born (=1)	-.0049
	(.0519)
P-value of joint F-test	0.000
N	1774

Notes: The table presents effects of each child-level characteristic on attrition among the sample, using different child-level characteristics as outcomes in each row. The independent variable is an indicator that equals 1 if a child was interviewed at baseline (2009 in Kenya, 2012 in Ethiopia), but not during the long-run follow-up survey round (2020 in Kenya and 2022 in Ethiopia). Mean differences and cluster standard errors at the household level (in parentheses) between the attrited and non-attrited children are reported. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. The p-value of the joint significance test for all variables across attrition is reported.

Table C2: Joint test of selective attrition

	Outcome: Attrition in the endline (=1)	
	(1)	(2)
Male (= 1)	-0.093***	-0.071*
	(0.020)	(0.038)
Age	0.038***	0.029***
	(0.004)	(0.010)
First born (=1)	0.005	0.105
	(0.033)	(0.123)
Second born (=1)	0.017	0.079
	(0.029)	(0.088)
Third born (=1)	-0.041	0.040
	(0.025)	(0.062)
F-statistics	25.368	6.817
p-value of joint significance	0.000	0.000
Household FE		✓
Observations	1774	1774

Notes: This table presents the effects of attrition on child-level characteristics. The outcome is an indicator equal to 1 if a child was interviewed at baseline (2009 in Kenya, 2012 in Ethiopia) but not during the long-run follow-up survey (2020 in Kenya and 2022 in Ethiopia). The sample is restricted to children who are in the main analysis sample (ages 6–20 in Kenya 2020 and 7–17 in Ethiopia 2022) and who were expected to have been born by the baseline (approximately age 9 in Kenya 2009 and age 7 in Ethiopia 2012). Reported are estimated coefficients with household-clustered standard errors in parentheses. * denotes significance at the 10% level; ** at 5%; and *** at 1%. The p-value from the joint significance test of all variables predicting attrition is also reported.

Table C3: Differential attrition by cumulative number of productivity shocks

	Outcome: Attrition (=1)	
	(1)	(2)
Cumulative number of positive shocks (5km)	-0.002	
	(0.027)	
Cumulative number of negative shocks (5km)	0.001	
	(0.027)	
Cumulative number of positive shocks (15km)		0.002
		(0.027)
Cumulative number of negative shocks (15km)		-0.003
		(0.027)
Observations	1493	1493

Notes: The table presents the effect of the cumulative number of positive and negative productivity shocks since 2000 during the study periods on attrition, where the outcome is an indicator that equals 1 if a child was interviewed at baseline (2009 in Kenya, 2012 in Ethiopia), but not during the endline survey (2020 in Kenya and 2022 in Ethiopia). Estimated coefficients and cluster standard errors at the community level (in parentheses) are reported in each column. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table C4: Effects of cumulative number of productivity shocks on fertility decisions and mortality

	Outcome: Number of school-aged children at endline	
	(1)	(2)
Cumulative number of positive shocks (5km)	0.163	
	(0.130)	
Cumulative number of negative shocks (5km)	-0.160	
	(0.130)	
Cumulative number of positive shocks (15km)		0.218
		(0.137)
Cumulative number of negative shocks (15km)		-0.215
		(0.137)
Observations	1493	1493

Notes: The table presents the effect of the cumulative number of positive and negative productivity shocks since 2000 during the study periods on the number of school-aged children at endline survey (2020 in Kenya and 2022 in Ethiopia). Estimated coefficients and cluster standard errors at the community level (in parentheses) are reported in each column. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.