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Weathering Conflict: The Effect of Resource Shocks on Livestock Raids

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Abstract

We examine the impact of climate shocks and drought insurance on inter-communal pastoral conflict in Kenya and Ethiopia. Using NASA's eMODIS satellite data on pasture availability and a 40-season longitudinal household dataset, our findings highlight the dual role of pasture scarcity and pasture abundance in driving conflict, contingent on seasonal timing. Negative shocks leading to pasture scarcity increase conflict in dry seasons, while positive shocks that lead to pasture abundance fuel conflict in subsequent rainy seasons. Leveraging exogenous variation in drought insurance, we find that while insurance reduces conflict on average, this masks important heterogeneity. *Ex post* indemnity payments mitigate conflict during droughts, but *ex ante* insurance coverage exacerbates conflict when pasture is abundant in rainy seasons. These findings highlight the dual relationship between resource availability and conflict, and the importance of considering the impact of policy interventions in this light.

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1 Introduction

A growing body of research examines the relationship between climate variability and conflict, highlighting the role of resource fluctuations as a key channel. One strand of the literature emphasizes the conflict-inducing effects of negative resource shocks (e.g., (Homer-Dixon, 1994; Von Uexkull et al., 2016; McGuirk and Nunn, 2024; Hsiang et al., 2011; Burke et al., 2015, 2024). For example, Harari and La Ferrara (2018) find that adverse weather shocks during the crop growth season lead to higher levels of conflict locally and in neighboring areas through spillover effects. Conversely, another strand of research finds that positive resource shocks – such as increased rainfall or pasture abundance – can also elevate conflict risk (e.g., (Collier and Hoeffler, 2004; Salehyan and Hendrix, 2014; Mack et al., 2021)). In the Sahel, for instance, Koren and Schon (2023) document a doubling of non-state violence during peak agricultural production periods. Although the empirical findings from these two literatures may appear contradictory, theory suggests that the underlying mechanisms differ. Scarcity-based explanations posit that negative shocks exacerbate competition over resources, increasing the likelihood of conflict, particularly in contexts where adaptive capacity is low (Homer-Dixon, 1994; Hidalgo et al., 2010; Cederman et al., 2013; Koubi, 2019). In contrast, theories of resource abundance argue that increased returns from violence or reduced opportunity costs of participation in armed conflicts can drive higher conflict incidence (Collier and Hoeffler, 2005; Schon et al., 2023; Koren and Schon, 2023; Crost and Felter, 2020; Ubilava et al.,

view Boards at Cornell University (Protocol ID No 0907000655, 1203002881, 2008009760) ILRI (IRB approval number: ILRI-IREC2015, ILRI-IREC2020-53), and NACOSTI (NACOSTI/P/20/7050). Data were collected by a consortium of the International Livestock Research Institute (ILRI), Cornell University, Syracuse University, the University of California at Davis, the University of Sydney, and the Institute of Developing Economies-JETRO, supported financially by the US Agency for International Development (USAID) Agreement No. LAG-A-00-96-90016-00 through Broadening Access and Strengthening Input Market Systems Collaborative Research Support Program (BASIS AMA CRSP), the Australian Department of Foreign Affairs and Trade through the Australia Development Research Awards Scheme award "The human and environmental impacts of migratory pastoralism in arid and semi-arid East Africa", JSPS Grant-in-Aid for Scientific Research (B)-26301021, the UK Department for International Development (DfID) through FSD Trust Grant SWD/Weather/43/2009, the Agriculture and Rural Development Sector of the European Union through Grant agreement No: 202619-101, USAID Grant No: EDH-A-00-06-0003-00, the World Bank's Trust Fund for Environmentally and Socially Sustainable Development (Grant No: 7156906), the CGIAR Research Programs on Climate Change, Agriculture and Food Security and Dryland Systems, the CGIAR Standing Panel on Impact Assessment, the CGIAR Research Program on Livestock, and the Foreign, Commonwealth & Development Office Project "Extreme Poverty - Building Evidence for Effective Action" through Oxford Policy Management Limited (Award Number: POR008864).

2023).[1]

In this paper, we examine how seasonal variability in pasture resources affects inter-communal livestock raiding among pastoralist households in Kenya and Ethiopia. Using data from 40 seasons, we analyze how both pasture scarcity and abundance influence conflict dynamics in the same households over time. Livestock raiding has long been a prevalent form of conflict in pastoral regions of Sub-Saharan Africa, but its frequency and intensity have escalated in recent decades (Schilling and Werland, 2023). Our findings reveal a dual role of resource fluctuations: negative shocks that lead to pasture scarcity increase raiding during dry seasons, while positive shocks that lead to pasture abundance heighten conflict in subsequent rainy seasons. We further explore the role of drought insurance as a policy intervention and find that, while insurance reduces conflict on average, its effects are heterogeneous. *Ex post* indemnity payments help mitigate conflict during droughts in dry seasons, yet *ex ante* insurance coverage leads to a behavioral response that amplifies conflict during pasture abundant rainy seasons. These findings contribute to the broader literature on climate, resources, and conflict by highlighting the variable nature of resource-driven violence and the resulting complex effects of financial interventions in conflict-prone settings.

Pastoralist communities in the Arid and Semi-Arid Lands (ASALs) rely heavily on livestock for their livelihoods, making them particularly vulnerable to climate variability. Rising temperatures and increasing drought frequency have intensified resource scarcity in these regions. The ASALs in East Africa experience four distinct seasons – two rainy and two dry – each shaping patterns of pastoral mobility and resource use. Pasture availability is generally sufficient for local grazing during rainy seasons, whereas dry seasons typically necessitate migration to more distant grazing areas (Tache and Oba, 2009; McPeak and Little, 2018). These movements occur in a context of persistent ethnic tensions, where disputes over resources frequently escalate into violent conflict. Livestock raiding, a long-standing practice in the region, plays a central role in these conflicts, particularly in areas with contested territorial claims (McPeak and Little, 2018). Raids often trigger retaliatory counter-raids, leading to cycles of violence with severe economic and social consequences, including loss of human life and depletion of livestock assets.

To examine the relationship between pasture variability and conflict, we construct a 40-season panel dataset of 1,586 pastoral households across 44 communities and six ethnic groups in the ASAL regions of Ethiopia and Kenya. We match these data to

[1] One component of this is that abundance in areas with harsh climatic conditions can finance and thereby enable and increase conflict for non-state actors (Schon et al., 2023). An extensive literature review can be found in the Appendix, see subsubsection 7.1.1.

monthly normalized difference vegetation index (NDVI) measures from NASA, a well-established proxy for pasture quality in these regions. NDVI values are aggregated spatially at the regional level and temporally from monthly to seasonal levels to align with the household panel structure. To define pasture shocks, we compute NDVI z-scores relative to historical averages for each region and season. A positive shock (resource abundance) is identified when the NDVI z-score falls in the top 20% of the historical distribution for that region and season, while a negative shock (resource scarcity) corresponds to the bottom 20%. The remaining seasons are classified as normal pasture conditions. Using household fixed effects, we estimate the effect of both positive and negative pasture shocks on the likelihood that a household reports livestock loss due to raiding. Our identification strategy leverages within-household variation over time, allowing us to isolate the impact of pasture fluctuations from time-invariant household characteristics.[2]

We find that livestock raiding occurs in both dry and rainy seasons but is more frequent during the latter. On average, the likelihood that a household reports being raided is 0.964% in the dry season and 1.271% in the rainy season. Our results indicate that both positive and negative shocks to pasture availability increase the likelihood of raiding, but through distinct mechanisms. Negative pasture shocks (resource scarcity) increase the probability of being raided by 65% relative to normal pasture conditions, from 0.554% to 0.917% (significant at the 5% level), with effects concentrated in dry seasons, where the likelihood more than doubles from 0.362% to 0.768%. In contrast, pasture scarcity during rainy seasons has no significant impact on raiding. Positive pasture shocks (resource abundance) do not have immediate effects, but instead shape conflict dynamics across seasons. Abundant pasture in a dry season increases the likelihood of raiding in the subsequent rainy season by 120%, from 0.715% to 1.57% (significant at the 1% level), even after controlling for rainy-season pasture conditions. Conversely, pasture abundance during a rainy season reduces raiding in the following dry season by 82% (significant at the 1% level), from 0.499% to 0.089%. We show that our results are robust to variations in the definition of variables and specifications. These findings suggest a seasonal pattern: resource scarcity drives conflict in dry seasons when competition for survival is highest, whereas resource abundance fuels conflict in rainy seasons by enabling raiding when the returns are higher.

Given that the drivers of conflict differ between contexts of pasture scarcity and pasture abundance, we also examine the impact of a policy intervention that has previously been shown to reduce conflict (Gehring and Schaudt, 2024; Sakketa et al.,

[2]We show robustness to alternative definitions of shocks in Table 12 and Table 13 in the Appendix, and results are qualitatively similar.

2024). Specifically, we analyze the effects of index-based drought insurance, which provides indemnity payments when pasture levels fall below a predefined threshold based on NDVI z-scores. Although the primary objective of this insurance is to buffer households against negative pasture shocks by alleviating resource scarcity – a mechanism that is confirmed by both Gehring and Schaudt (2024) and Sakketa et al. (2024) – it may also have behavioral effects by altering risk-taking incentives. Prior research suggests that insurance coverage can reduce *ex ante* risk exposure, leading households to adopt higher-risk, higher-return production strategies (Jensen et al., 2017; Matsuda et al., 2019; Barrett et al., 2024). We exploit the randomized introduction of the insurance program to estimate the effects of insurance coverage and indemnity payments on the likelihood of raiding. Using randomly allocated discount vouchers as an instrument, we estimate the Local Average Treatment Effect (LATE) of receiving indemnity payments as well as being covered by insurance on the likelihood of being raided. This approach allows us to disentangle the *ex ante* behavioral effects of insurance coverage from the *ex post* impact of indemnity payments, providing new insights into the role of financial interventions in shaping conflict dynamics.

Overall, households with drought insurance experience a 1.996 percentage points (p-value$<$0.1) lower likelihood of experiencing losses due to raiding, which corresponds to an intent-to-treat effect of 0.868 percentage points, a 113% reduction relative to the control mean. However, we show that this masks important heterogeneity. During dry seasons, the effect of insurance is entirely driven by indemnity payments, which reduce losses from raiding by 8.8 percentage points (p-value$<$0.05), which translates into a reduction of 60.22% in the likelihood of losses due to raiding across the entire sample (ITT 0.264%). During rainy seasons, however, the effect is entirely driven by insurance coverage, which reduces the likelihood of losses due to raiding by 3.5 percentage points (p-value$<$0.1), corresponding to a 175% reduction across the sample (ITT 1.52%). If we next consider the interaction between insurance and pasture shocks, we find that the effect of indemnity payments, which explains the effect of insurance in dry seasons, becomes stronger during bad pasture shocks in dry seasons. This clearly stresses the mitigating role of indemnity payments in preventing resource-scarcity driven conflict. We, however, also find that the effect of insurance during positive pasture shocks leading to pasture abundance in rainy seasons, however, is orthogonal to the effect of normal and bad pasture during rainy seasons: While insurance generally reduces the likelihood of losses due to raiding in rainy seasons in the sample by 175%, it increases this likelihood during positive pasture shocks, which we suggestively attribute to the potential behavioral effects of *ex ante* insurance coverage, incentivizing higher-risk but higher-return strategies.

Our study contributes to the literature on resource scarcity, resource abundance, and conflict (Collier and Hoeffler, 2005; Harari and La Ferrara, 2018; Opiyo et al., 2015; Van Baalen and Mobjörk, 2018; Burke et al., 2015, 2024; McGuirk and Nunn, 2024) by providing micro-level evidence on how both resource scarcity and abundance can increase the likelihood of conflict within the same household, dynamically over time. While previous studies document the link between climatic shocks and violence, much of the existing evidence relies on administrative or event-level datasets – such as the Armed Conflict Location & Event Data Project (ACLED) – which, while valuable for identifying large-scale patterns, often fail to capture localized conflicts or the dynamic effect of fluctuations in resources on households over time.[3] Prior qualitative research (Abdela, 2024)) documents that herders report to collaborate more with other groups during droughts, e.g., via sharing pasture lands and water resources, than during periods of normal pasture. The authors explain that if conflict does arise during droughts, as we show in our results, this is because they are forced to engage in strategies that are *necessary* for survival, such as encroaching on contested lands in search of pasture, or theft of resources, to maintain their main source of livelihood.[4] We also show that conflict during rainy seasons is higher than during dry seasons, and that the likelihood to be raided is heightened during good pasture shocks in rainy seasons. This is consistent with an interpretation whereby livestock are healthy due to good pasture, which increases their mobility during such periods, with higher returns to raiding(Scoones, 2023; Witsenburg and Adano, 2014).

We contribute to the emerging literature on insurance as a tool for mitigating conflict. Recent work by Gehring and Schaudt (2024) shows that insurance uptake reduces farmer-herder conflict in Kenya, while Sakketa et al. (2024) provide evidence that it also reduces conflict between different pastoral ethnic groups in Ethiopia. Our study is closest to Sakketa et al. (2024), who find that insurance reduces conflict among pastoralist communities in southern Ethiopia over ten seasons (using ACLED data), with stronger effects in periods of below-average precipitation. They argue that insurance uptake is particularly effective in mitigating conflict 30 to 60 kilometers from homesteads, where pastoralists are likely to graze and access water points during dry seasons. We extend this literature by demonstrating that insurance reduces conflict on average and masks important heterogeneity, consistent with different effects of resource scarcity and resource abundance on conflict. Our findings suggest that *ex post* indemnity payments reduce resource-scarcity driven conflict in dry seasons. However, behavioral effects of *ex ante* coverage lead to increases in

[3]See e.g. Burke et al. (2024) for an overview. See (Sakketa et al., 2024) for an overview of the limitations of ACLED, e.g., its reliance on journalism.

[4]See also (Sakketa et al., 2024).

conflict during periods of pasture abundance during rainy seasons. We suggest these effects are similar to *ex ante* effects observed in Karlan et al. (2014); Jensen et al. (2017); Cole and Xiong (2017); Hill et al. (2019); Matsuda et al. (2019); Boucher et al. (2021); Stoeffler et al. (2022); Barrett et al. (2024), suggestively arising because of increased incentives to invest in higher-risk but higher-return strategies when households are covered by insurance.

2 Context

Our study locations are pastoral communities in Marsabit County, Kenya, and Borana Zone, Ethiopia. These areas have sparse vegetation levels, implying limited opportunities for sedentary agriculture and other land-based means of production. Therefore, the populations living in these areas depend primarily on livestock rearing for their livelihood. Pastoral herds consist of cattle, camels, sheep, and goats. The average herd during the period 2009 to 2022 consists of the equivalent of 25 cattle (see Table 1).[5] The composition in cattle equivalents was 26% cattle, 32% camels and 42% goats/sheep in our Kenyan sample and 76% cattle, 9% camels and 15% goats/sheep in our Ethiopian sample.

The region experiences a bimodal rainfall pattern consisting of two rainy seasons– the March-May period is often called the long rain (LR) season and October-December the short rain (SR) season. Each rainy season is followed by a dry season–January-February is the short dry (SD) season and June-September is the long dry (LD) season. These four seasons are often grouped into the long rain-long dry season (March - September) and the short rain-short dry season (October - February). In the rainy seasons, because pasture availability is comparatively high, pastoral households can herd near their basecamps, where their (semi-)permanent homes are and where the women, children, and elders reside. In dry seasons, groups of (young) men, usually from the same community, typically migrate with their livestock in search of pasture and water, often several hours to days of travel by foot from the basecamp to so-called satellite camps. In case of exceptionally low pasture availability, they migrate to other areas for fodder and water, including areas with disputed (informal) ownership.

[5]Note that the selection of the sample is random conditional on strata of the number of animals in herds.

Table 1: Descriptive Statistics

	mean	sd	min	max
No. of household members (discrete)	10.692	6.22	1	30
Male headed household (binary)	0.669	0.47	0	1
Tropical Livestock Units owned (decimal)	24.748	35.87	0	725
Share of cattle in TLU (proportion)	0.318	0.37	0	1
Share of camels in TLU (proportion)	0.290	0.32	0	1
Share of goats/sheep in TLU (proportion)	0.392	0.33	0	1
Moved livestock to sattelite camp in the previous season (binary)	0.694	0.46	0	1
No. of livestock loss events per season (discrete)	1.496	0.83	1	9
No. of livestock loss events due to starvation or droughts per season (discrete)	0.569	0.83	0	7
No. of livestock loss events due to rain per season (discrete)	0.045	0.23	0	3
No. of livestock loss events due to raiding/rustling/conflicts per season (discrete)	0.017	0.14	0	3
No. of livestock loss events at the satellite camp per season (discrete)	0.293	0.61	0	7
IBLI coverage this season (binary)	0.056	0.23	0	1
IBLI payout received this or in the previous season (binary)	0.041	0.20	0	1
Lost animals due to raiding in a rainy season (binary)	0.009	0.09	0	1
Lost animals due to raiding in a dry season (binary)	0.005	0.07	0	1
Has ever lost an animal due to raiding (binary)	0.122	0.33	0	1
Observations	28485			

Notes: This table presents the mean, standard deviation, minimum value, and maximum value (Columns 1-4, respectively) and the number of observations in total (bottom row). These are the averages across the entire panel, representing 7 rounds in Kenya between 2012 and 2020 and 5 rounds in Ethiopia between 2015 and 2022. These values are measured at the annual level unless otherwise specified. *Has ever lost an animal due to raiding* is 1 if the household has lost an animal due to raiding in any of the survey rounds. All binary variables are 1 if the statement applies and 0 otherwise. The proportional shares of cattle, camels and goats/sheep refer to the animals owned by the household and add up to 1, unless the household does not own any livestock, in which case this variable is omitted. All discrete variables required answers with increments of 1. TLU are tropical livestock units, with a cow being 1 TLU, a camel 1.4 TLU, and a goat or sheep 0.1 TLU. TLU, therefore, has increments of 0.1.

Extensive livestock production is the most efficient use of these drylands, but it makes this population heavily dependent on the climatic conditions (Jensen et al., 2024; McPeak et al., 2011). Weather impacts the vegetation levels and water supply essential to successful livestock rearing. Droughts lead to shortages of food and pasture. Hence, livestock is weakened or dies. Table 1 shows that for the duration of the survey, starvation and drought were by far the most-often cited causes for loss of livestock, with households reporting 0.57 TLU lost due to droughts or starvation per season on average.

The locations of our study, Marsabit County and Borana Zone, are home to various ethnic groups practicing pastoralism, notably the Borana, Burji, Gabra, Samburu, Turkana, and Rendille. These groups have different languages, customs, and livestock preferences. Whereas the Samburu, Turkana and Borana are generally known as cattle-rearing pastoralists, the Gabra and Rendille known as camel-rearers, although this highly varies within these ethnic groups depending on where the communities are settled and operating (Fratkin, 2001).

Conflict in the form of livestock raiding is a historical practice in these areas and involves the (violent) taking of livestock by young men (commonly 15-30 years old) from other communities. It is a cultural practice that brings honor to those who take large numbers of livestock (Schilling et al., 2012). A livestock raid of group A on group B is often followed by a counter-raid of group B on group A. Hence, a vicious cycle of violence is instigated. Often convened by elders, peace councils traditionally aim to break these cycles through dialogue, restitution of stolen livestock, and reparations (Mussa et al., 2017; Klopp et al., 2010)

Schilling et al. (2012) describes that resource scarcity, particularly droughts, can drive young herders to steal livestock to compensate for the animals they have lost to hunger or thirst. These can either be returned to their homestead ("restock") or sold to offset lost income. Sakketa et al. (2024) suggest that herders with no intention of raiding put themselves at additional risk of being raided by adopting herd survival tactics such as grazing in disputed areas, which increases their propensity to be raided.

Historically, raids were primarily motivated by the need to access pastures/water points, replenish livestock and accumulate wealth for dowry and bride price payments (Likaka and Muia, 2015; Wonbera, 2024). While these factors remain central drivers of raiding activity, contemporary dynamics suggest that a broader set of motivations, including territorial claims and competition over land, have gained equal significance (Okumu, 2021). Notably, the scale of livestock theft has reportedly escalated in recent years, paralleled by a marked increase in the intensity and frequency of violent conflicts associated with such raids (Schilling and Werland, 2023; Schilling and Akuno, 2013; Greiner, 2013). Qualitative literature suggests that this intensification may be attributed to increased climatic variability, the proliferation of modern firearms (Greiner, 2013; Schilling and Akuno, 2013), increased pressure on wealth (Schilling and Akuno, 2013), commercialization, and land pressures (Cline, 2020).

Mathew (2022) and McCabe et al. (1999) suggest that the proximity of herders to rival ethnic or clan groups is a primary catalyst for raids, as it facilitates contact and heightens perceived threats or opportunities for raiding. This closeness increases the likelihood of hostile encounters, as it often serves as the main justification for calling raids, driven by the competition over resources or the need for preemptive retaliation.[6]

2.1 The Role of Insurance

Index-Based Livestock Insurance (IBLI) was developed by a consortium of researchers led by the International Livestock Research Institute (ILRI) to protect pastoralists in Kenya and Ethiopia against climate-related risks, particularly drought. IBLI is an insurance product designed for pastoralists in the arid and semi-arid lands (ASALs) of Sub-Saharan Africa and was first sold by a local firm in 2010 in Kenya. Unlike traditional indemnity insurance based on actual losses, IBLI uses the Normalized Difference in Vegetation Index (NDVI) to determine pasture quality conditions and calculate indemnity payments for policyholders if the pasture falls below a certain threshold, which is set based on historical pasture realizations. Payouts are scaled by the relative severity of conditions and the amount of coverage purchased in units of Tropical Livestock Units (TLU).[7]

In expectation, however, the direction of the effect of drought insurance on conflict is ambiguous. Insurance may have an effect on conflict, both through its *ex ante* behavioral effects and *ex post* indemnity payments. Insurance may reduce the need to adopt risky mitigation strategies during droughts because pastoral households are able to keep their cattle alive through the *ex post* payments or by *ex ante* diversification into more drought-resistant livelihood strategies (Sakketa et al., 2024; Cole et al., 2017; Jensen et al., 2017; Taye, 2023). However, insurance could also increase conflict by lowering the economic risk of cattle rearing through *ex ante* coverage, e.g., leading to an increased number of cattle putting pressure on already scarce resources (Jensen et al., 2017) or through wealth effects that decrease the relative risk aversion of households covered by *ex post* indemnity payments (Heinemann, 2008; Paulsen et al., 2012). Furthermore, formal insurance, either through coverage or ex post indemnity payments, may crowd-out informal insurance (Cecchi et al., 2016; Anderberg and Morsink, 2020), which may serve as the social fabric of communities. Eroding it can potentially increase conflict, although Takahashi et al. (2019) find

[6]See (Mathew, 2022) for an elaborate illustration and anthropological analysis of the reasoning behind decisions to call for and join raids.

[7]A cow represents 1 TLU, a camel is 1.4 TLU and a goat or sheep are 0.1 TLU. See more details here.

that index insurance crowds-in informal risk-sharing. Both Sakketa et al. (2024) and Gehring and Schaudt (2024) have discussed the effects of drought index insurance on conflict, both finding that higher insurance uptake decreases aggregate conflict, both between pastoral groups and between pastoralists and sedentary farmers, respectively. Sakketa et al. (2024) also show that insurance coverage for the entire herd leads to a 4.9 percentage points decrease in the likelihood of a household member migrating for pasture and water, indeed suggesting that the decrease in conflict is likely due to the decreased need for risky mitigation strategies.

3 Data

This paper leverages data from two sources to examine the impact of weather shocks on raiding. The first source is publicly available vegetation quality data derived from the National Aeronautics and Space Administration (NASA) satellite imagery. The second source is a longitudinal household-level dataset from Marsabit County, Kenya, and Borana Zone, Ethiopia, collected through several collaborations led by the International Livestock Research Institute (ILRI).

3.1 NDVI z-scores

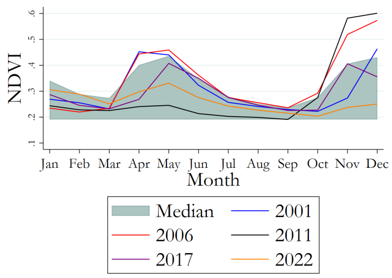
To construct measures of resource quality, we use the within-region monthly z-score of the Normalized Difference in Vegetation Index (NDVI) which has been demonstrated to be a reliable signal of forage availability (Meroni et al., 2014). NDVI data, which are based on data acquired by MODIS sensors aboard Terra and Aqua satellites, are available a 250x250m at 10-day intervals globally from NASA/USGS.

The absolute NDVI scores by Division in Kenya are presented in Figure 1,[8] and by Woreda in Ethiopia in Figure 2.[9] These visualizations reveal several key patterns. First, they demonstrate that the seasonal demarcations generally align with variations in pasture levels, with less pasture in the months constituting dry seasons and more pasture in the months constituting rainy seasons. Second, these patterns highlight that generally, rainy seasons with good pasture levels precede dry seasons with comparatively better pasture. However, the patterns also highlight that there is still substantial variation in dry seasons, even for similar prior rainy seasons. The absolute variance in dry-season pasture is considerable, and in most cases - particularly

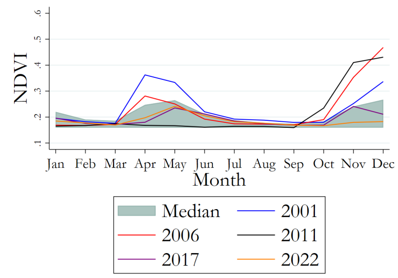
[8] Note that before administrative changes, the current Divisions Central and Gada were combined into Central & Gada. Hence, their NDVI z-scores are calculated jointly.

[9] These graphs are inspired by Vrieling et al. (2016).

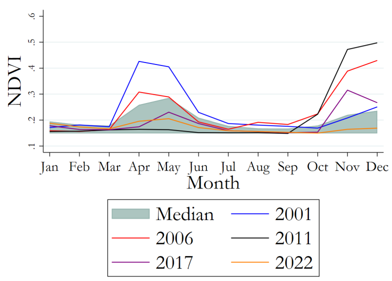
in Ethiopia – a measurable level of pasture remains consistently present. Therefore, we choose to define both pasture scarcity and pasture abundance at the season level, where it should be noted that pasture scarcity in dry seasons, but not necessarily in rainy seasons, constitutes a drought.[10] Finally, the high variability in absolute NDVI scores across different locations underscores the necessity of incorporating z-scores both by location and across time, making NDVI a valuable independent variable with sufficient variance to inform predictions.



(a) Central & Gada



(b) Laisamis



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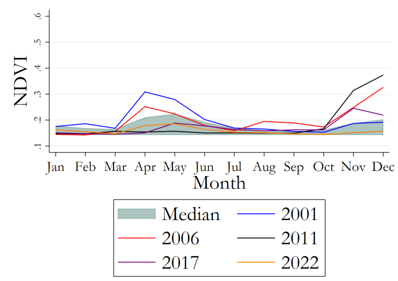
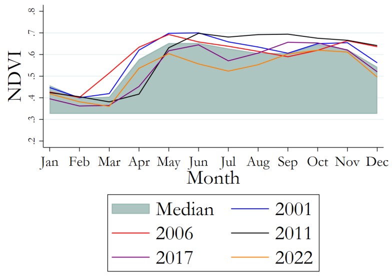


(d) Maikona

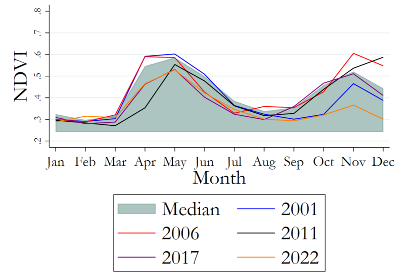
Figure 1: NDVI per Month Across Divisions for Various Years

These graphs show the spatially aggregated absolute NDVI index levels by Division in Marsabit, Kenya across five different years. It represents the "greenness" by presenting the ratio between red and near-infrared values. It indicates the vegetation levels and health. The NDVI ranges from -1 to 1 (below zero refers to the absence of land, zero refers to land without vegetation, and one refers to dense and healthy vegetation). Data is derived from NASA's MODIS satellite. The shaded green presents the median, and the lines the different years.

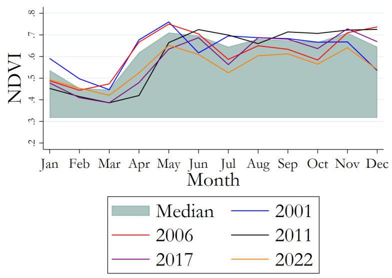
[10]Vrieling et al. (2016) have chosen to focus exclusively on rainy-season NDVI z-scores for the design of IBLI, as their selected years and regions show a strong correlation between the rainy and dry seasons. This approach also allows for more precise and timely indemnity payment calculations, which was a priority for their study, whereas this paper aims to explore heterogeneity across seasons.



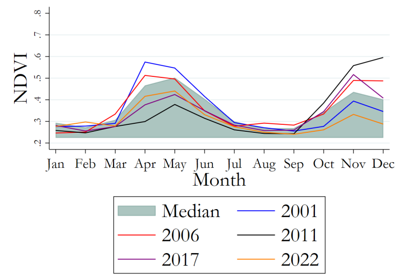
(a) Arero



(b) Dhas



(c) Dillo



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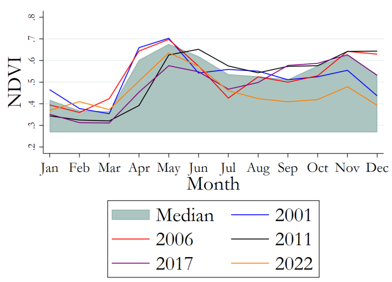
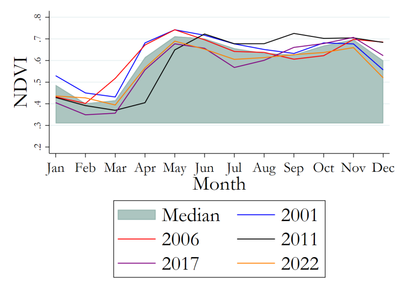
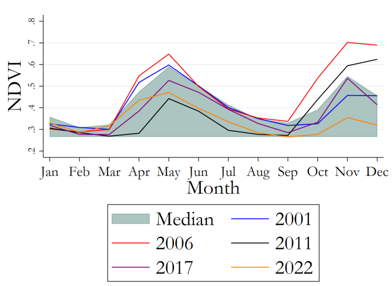


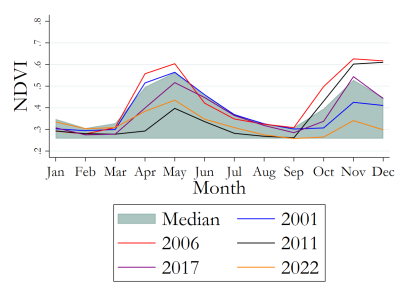
(e) Moyale



(f) Teltele



(g) Yabello



(h) Miyo

Figure 2: NDVI per Month Across Woredas for Various Years

These graphs show the spatially aggregated absolute Normalized Difference in Vegetation (NDVI) index levels in Borana Zone, Ethiopia across five different years. It represents the "greenness" by presenting the ratio between red and near-infrared values. It indicates the vegetation levels and health. The NDVI ranges from -1 to 1 (below zero refers to the absence of land, zero refers to land without vegetation, and one refers to dense and healthy vegetation). Data is derived from NASA's MODIS satellite. The shaded green presents the median, and the lines the different years. This shows the variance in vegetation levels, as well as monthly and seasonal patterns by Woreda.

To construct the seasonal measures of pasture scarcity and abundance, we first aggregate the monthly NDVI values spatially by Division in Kenya and Woreda in Ethiopia.[11] Subsequently, this monthly mean is aggregated (temporally) to a seasonal value.[12] Next, the z-scores are calculated for that region and that season, based on the historical mean and standard deviation for that specific season in that region since 2000 (the first year this satellite was operational), as in Equation 1. This paper includes data from 2000 to 2023, which corresponds to 92 seasons. This estimation approach follows Vrieling et al. (2016).

$$NDVIz_{pm} = \frac{NDVI_{pm} - \mu_{pm}}{SD_{pm}} \tag{1}$$

In Kenya, the NDVI z-scores of various Divisions are moving in tandem, ranging from -1.648 to 3.480, with a mean of 0.135 and a standard deviation of 1.135. This is visualized in Figure 5 in the Appendix. Although the pattern of NDVI z-scores across Divisions seems similar, the extremes vary per Division, which can substantially affect pastoralists' experiences. As explained, several years passed between the 6th and 7th round of the household panel data collection, explaining the gap between 2016 and 2019. In Ethiopia, the NDVI z-scores range from -2.289 to 2.479, with a mean of 0.0036 and a standard deviation of 0.884, as seen in Figure 6 in the Appendix. The gap between the 4th and 5th rounds of IBLI data collection explains the lack of observations between 2016 and 2019.

[11] Versions with Sublocations and Kebeles rather than Divisions and Woredas are also created as a robustness check, see Table 14.

[12] A pixel of the Terra MODIS, the eMODIS approximation for land masses, is approximately 0.25x0.25 km at the equator and, hence, for our study area.

3.1.1 Independent variable: Pasture Quality

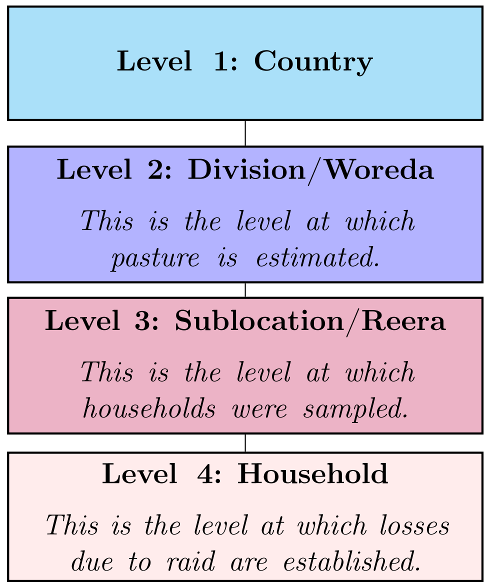
To construct the dummies of good, bad, and normal pasture quality, we distinguish three levels of pasture availability per season. These are restricted by the z-score value relative to all z-scores registered by the eMODIS satellite (including those not in the IBLI panel dataset time frame) in the same type of season (i.e., SD/LR/LD/SR) in the same region between 2001 and 2022. The lowest 20% of seasons in a region is defined as a bad pasture quality season. The top 20% NDVI z-scores of a season in a region are classified as good quality seasons. The remainder of the seasons are classified as normal seasons.[13] See Figure 7 in the Appendix for the occurrence of each type of season by region in our sample.

3.2 IBLI panel data

The IBLI household panel survey was designed to collect household panel data before, during, and after the implementation of IBLI between 2009 and 2022. It collects indicators of livestock production, income, consumption, migration, and risk management. The IBLI survey is conducted annually but also gathers season- or monthly-specific information on livestock production and losses. Monthly data is aggregated temporally to the four seasons as demarcated previously. The data set includes 1,586 pastoral households from 21 communities in five Kenyan Divisions and eight Ethiopian Woredas. For an overview of the administrative structure used in this paper and how they are used in our analysis, see Figure 3. In Marsabit, seven rounds of data were collected, the first six were collected annually between 2009 and 2015, and then a final survey was conducted in 2020. In Borana, Ethiopia, five rounds of data were collected, the first four were collected annually from 2012 to 2015, and a final round was collected in 2022. The timing of these can be found in Table 7. Household sampling for the survey was done at the Reera level in Ethiopia and the Sublocation level in Kenya. Households were selected by stratifying on TLU class, with 1/3 of households in the sample having less than 10 TLU, 1/3 having between 10 and 20 TLU, and 1/3 having more than 20 TLU. In Marsabit, this panel includes 1,062 households during 34 seasons, and in Borana, 524 households during 20 seasons.

[13] For further explanation of IBLI payouts, see `https://ibli.ilri.org/`.

Figure 3: Administrative structure in both Kenya and Ethiopia



Notes: These areas are arranged from highest to lowest aggregation level. "Division" (level 2) and "Sublocation" (level 3) refer to administrative areas in Kenya, and "Woreda" (level 2) and "Reera" (level 3) in Ethiopia.

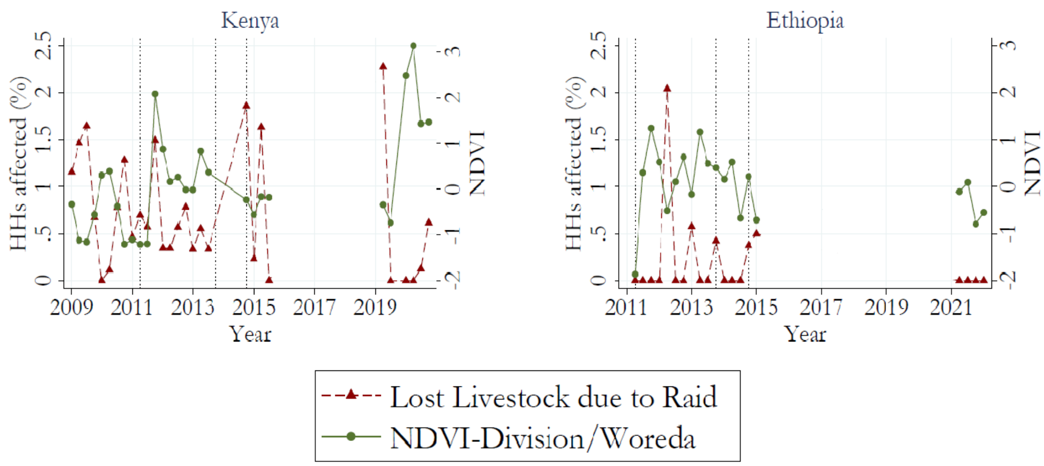
3.2.1 Dependent variable: livestock loss due to raiding

To estimate conflict, we use a seasonal variable indicating that the household reported losing livestock due to raiding in this season. Respondents are first asked if they lost any animals during a specific season other than for slaughter for their consumption. Subsequently, each loss event is queried: the number of animals, what type of animal, what month of what year the loss occurred, whether it occurred in the base camp or satellite camp, and the reason for this loss.[14] We use a binary variable that takes the value one in case any loss event has occurred in a season due to raiding, rustling, or conflict, and zero otherwise.

The NDVI z-scores and the binary seasonal loss of livestock due to raiding are plotted by country in Figure 4. These figures suggest an average negative correlation: the lower the pasture level, the higher the propensity to be raided and *vice versa*.

[14]The possible reasons listed are losses due to Starvation/Drought, Disease, Predation, Raiding/Rustling/Conflict, Accident/Poisoned, Rain, Old Age, Premature birth, or Just Lost.

Figure 4: NDVI and Having Lost Livestock due to Raiding per Season per Woreda or Division



Notes: The x-axes represent the years in which Kenya and Ethiopia, in the left and right figure respectively, were surveyed in the IBLI survey. The left y-axes represent the number of households affected by having lost livestock due to raids in the years as represented by the red dotted lines. The right y-axes show the average NDVI z-scores by Divison in Kenya and Woreda in Ethiopia, as represented by the green line. The gap between 2015 and 2019 in Kenya and 2015 and 2021 in Ethiopia is because there was no IBLI data collection in these periods.

Table 1 presents descriptive statistics for the household sample. These are the means (annually, unless indicated otherwise) across all periods from 2009 to 2022 that are included in the IBLI household survey (see Table 7 for an overview of the surveyed years per country). Table 1 shows that the average number of Tropical Livestock Units (TLU) owned by households is 25.[15] Per season, households reported an average of 1.5 TLUs lost. The largest share is due to starvation or droughts, with about 0.57 TLUs lost on average. 12% of households have reported to have lost livestock due to raiding or conflict at least once across all seasons included in the panel.

[15]Table 5 and Table 6 in the Appendix provide this data by country.

3.2.2 IBLI coverage and indemnity payments

We also exploit additional variation from insurance coverage and indemnity payments. An IBLI contract covers four subsequent seasons and is bought at the start of the short or long rainy season. After the introduction (from round 2 of the IBLI panel household survey), on average, 6.56% of households had IBLI coverage every year. Indemnity payments were observed in 40% of the seasons, made to those with IBLI coverage for that season. Discount coupons were randomly distributed to 60% of households in Kenya and 80% of households in Ethiopia every round, to randomly encourage take up. The timing of the survey rounds, randomized discount coupons, indemnity payments, and the contract shifts for Kenya and Ethiopia separately can be found in Table 7 in the Appendix.

Insurance is sold immediately prior to the start of the rainy seasons and covers four seasons. We define insurance coverage as a binary variable that is 1 if the household is covered by insurance in a particular season. Index triggers are determined using a pasture index in both countries, but the underlying data structure differs across countries. In Ethiopia, the trigger is met if the pasture index falls below the 20th percentile of the historical NDVI z-score distribution within a given insurance area. In Kenya, the index, derived from the same underlying pasture data, directly reflects predicted livestock mortality due to drought. The index is triggered when the predicted mortality rate is higher than 15% (up to 2012) or higher than 20% (from 2012 onward). The triggers are calculated based on NDVI data in the rainy season, for indemnity payment in the following dry season (Vrieling et al., 2016). This is to ensure that indemnity payments are received by the time the drought is severe, and can successfully protect livestock. We thus construct the variable "index triggered" as a binary variable that is 1 in dry seasons if an indemnity payment was triggered in that dry season. The same variable is also coded as 1 in rainy seasons if an indemnity payment was triggered in the preceding dry season. Otherwise, this variable is coded as zero.[16] The variable "indemnity payment" is coded as 1 in dry seasons if a household is covered by insurance in a particular season, and the index was triggered during that season. The variable is coded as 1 in rainy seasons if a household was covered by insurance in the prior dry season, and the index was triggered during the prior dry season. This is justified by indemnity payments typically arriving either at the end of the dry season or at the start of the subsequent rainy season.

[16] This implies that effects of index triggers need to be separately estimated, and the estimated effects do not sum to an aggregate effect.

4 Empirical Strategy

The effect of weather shocks on having lost livestock due to raiding each season is estimated using household-fixed-effects regressions following Equation 2, consistent with Equation 3 in Burke et al. (2024). Good pasture shocks and bad pasture shocks are compared to normal pasture conditions.

$$\begin{aligned} \text{LossRaid}_{hit} = \beta_0 &+ \beta_1(\text{Bad Pasture}_{it}) + \beta_2(\text{Good Pasture}_{it}) \\ &+ X_{hit} + \mu_h + \epsilon_{hit} \end{aligned} \tag{2}$$

LossRaid_{ht} is the dependent variable, that indicates whether household h in Woreda/Division i experienced livestock loss due to conflict during season t. The variables Bad Pasture and Good Pasture are one if the pasture quality in the Woreda or Division i during a season t is below the 20th percentile of the historical pasture distribution for that season for bad pasture and above the 80th percentile of the historical pasture distribution for that season for good pasture, and zero otherwise. X_{hit} represents a matrix of time-varying control variables for household h in Woreda/Division i in season t. We include household fixed effects μ_h to control for time-invariant household characteristics that might affect the propensity to be a victim of conflict. ϵ_{hit} represents the error term. Standard errors are bootstrapped with 1000 iterations. We also replace the Good and Bad pasture variables with their lags to estimate the effects of pasture levels in the previous season. Furthermore, and consistent with Equation 4 in Burke et al. (2024), we estimate the effect of concurrent and lagged pasture quality jointly:

$$\begin{aligned} \text{LossRaid}_{hit} = \beta_0 &+ \beta_1(\text{Bad Pasture}_{it}) + \beta_2(\text{Good Pasture}_{it}) \\ &+ \beta_3(\text{Bad Pasture}_{it-1}) + \beta_4(\text{Good Pasture}_{it-1}) \\ &+ X_{hit} + \mu_h + \epsilon_{hit} \end{aligned} \tag{3}$$

We also test the effect of insurance coverage and indemnity payments on losing livestock due to raiding. As insurance uptake and, thus, indemnity payments are plausibly endogenous, we predict insurance coverage by using randomly distributed discount coupons as an instrument. In the first stage, we estimate the predicted insurance coverage I, using a fixed-effects logit model:

$$\widehat{\mathrm{I}}_{ht} = \alpha + \beta_1 \text{CouponYear}_{ht} + \gamma \text{Season}_t + \varepsilon_{h,t} \tag{4}$$

where I_{ht} is an indicator for whether household h at time t purchased insurance, CouponYear_{ht} is a dummy indicating whether the household received a discount coupon, Season_s represents season fixed effects, μ_h are household fixed effects, and ε_{ht}

is the error term. From this regression, we obtain the predicted insurance coverage, denoted as $\widehat{\mathrm{I}}_{ht}$. To estimate the effect of insurance in the second-stage, we add the predicted insurance coverage, as in Equation 5:

$$\text{LossRaid}_{ht} = \beta_0 + \beta_1 \widehat{\mathrm{I}}_{ht} + \gamma \text{Season}_t + \mu_h + \varepsilon_{ht} \tag{5}$$

To estimate the effect of insurance coverage and indemnity payments, we interact the predicted insurance coverage with a binary variable that is plausibly exogenous that indicates whether the index in an index unit, u, was triggered, providing an interaction that can be interpreted as the predicted indemnity payment.

$$\text{LossRaid}_{hut} = \beta_0 + \beta_1 \widehat{\mathrm{I}}_{hut} + \beta_2 \text{Trigger}_{ut} + \beta_3 \widehat{\mathrm{I}_{hut}} \times \text{Trigger}_{ut} + \gamma \text{Season}_t + \mu_h + \varepsilon_{hut} \tag{6}$$

where LossRaid_{hut} represents the raid loss for household h in index unit u at time t, $\widehat{\mathrm{I}}_{ht}$ is the predicted insurance coverage from the first-stage. The effect of an indemnity payment is provided by $\beta_1 + \beta_3$, and is the combined effect of a household being insured and receiving an indemnity payment. Other variables are defined as above.

To explore the interaction between shocks and insurance, we estimate the following equation:

This model is specified as follows:

$$\begin{aligned} \text{LossRaid}_{hiut} = \rho_0 &+ \rho_1 \widehat{\mathrm{I}}_{hiut} + \rho_2 \text{Bad Pasture}_{it} + \rho_3 \text{Good Pasture}_{it} + \\ &\rho_4 \widehat{\mathrm{I}}_{hiut} \times \text{Bad Pasture}_{it} + \rho_5 \widehat{\mathrm{I}}_{hiut} \times \text{Good Pasture}_{it} + \\ &\rho_6 \widehat{\mathrm{I}}_{hiut} \times \text{Trigger}_{ut} + \rho_7 \widehat{\mathrm{I}}_{hiut} \times \text{Trigger}_{ut} \times \text{Bad Pasture}_{it} + \\ &\rho_8 \widehat{\mathrm{I}}_{hiut} \times \text{Trigger}_{ut} \times \text{Good Pasture}_{it} + \rho_9 \text{Trigger}_{ut} + \\ &\rho_{10} \text{Trigger}_{ut} \times \text{Bad Pasture}_{it} + \rho_{11} \text{Trigger}_{ut} \times \text{Good Pasture}_{it} + \\ &\gamma \text{Season}_t + \mu_h + \epsilon_{hiut}. \end{aligned} \tag{7}$$

where LossRaid_{hiut} represents the raid loss for household h in Division/Woreda i in index unit u at time t. Other variables are as specified above. Results from this last regression should be interpreted as suggestive, as the trigger and bad pasture shocks are significantly correlated at 0.39, raising a potential concern with multicollinearity of the bad pasture and trigger variables.[17]

[17] The correlation is imperfect because the Division/Woreda and index unit span different geographical areas, they are generated based on different historical distributions and the cut-off value to determine a trigger is different from the cut-off value used to determine a bad pasture shock.

5 Results

5.1 Pasture Quality and Livestock Losses due to Raiding

Households report losing livestock due to raids in both dry and rainy seasons, but the likelihood of losses is significantly higher during rainy seasons (87%). On average, across all seasons, a one z-score increase in NDVI of the area (Division/Woreda level) leads to a 23.80% decrease in the likelihood of losing livestock due to raiding significant at the 1% level ($p = 0.001$). Our results in Table 2 show that this masks important heterogeneity. Columns 1 to 3 of Table 2 present the effect of pasture quality in the current season on livestock losses due to raids in the same season, estimated following Equation 2. The coefficients represent the difference in the likelihood of losing animals due to a raid between a bad (good) pasture season and a normal season. The mean in the bottom row represents the likelihood of losses due to raiding under normal pasture conditions. Column 1 shows the effects of pasture quality across all seasons. These results suggest that across all seasons, bad pasture increases the likelihood of losing animals due to raiding by 0.4 percentage points, significant at the 5% level, an increase of 65% relative to normal pasture conditions. Column 3 shows that this is particularly pronounced in the dry seasons, when absolute pasture levels are generally lower. However, the effect is not significantly different from that during the rainy seasons.

Given that the quality of rainy seasons specifically are not only critical for pasture conditions, but also animal health in subsequent dry seasons, we also investigate the lagged effect of pasture shocks in prior seasons on raiding in current seasons. These results are shown in Columns 4-6. We see that it is not a bad pasture shock in a prior season but a good pasture shock in a prior season that drives conflict. Bad pasture has no significant effect on the propensity to be raided in the subsequent season. Column 4 shows that good pasture significantly increases the propensity to be raided in the subsequent season, with an increase of 55% compared to normal prior seasons. In Columns 5 and 6 we split the seasons by rainy and dry seasons, which demonstrates heterogeneity. While the effect of good pasture during a dry season on the propensity to be raided in the subsequent rainy seasons remains significant, the point estimate becomes substantially larger: the likelihood of losses due to raiding is increased by 0.856 percentage points, significant at the 1% level, a 120% increase relative to prior normal dry seasons.

Table 2: The Effect of Pasture quality on Losing Livestock due to Raids

	All Seasons	Rainy	Dry	All Seasons	Rainy	Dry	All Seasons	Rainy	Dry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Raided	Raided	Raided	Raided	Raided	Raided	Raided	Raided	Raided
Bad Pasture (v Normal Pasture)	0.00363**	0.00370	0.00406**				0.00379**	0.00213	0.00364*
	(0.00153)	(0.00243)	(0.00183)				(0.00154)	(0.00241)	(0.00186)
Good Pasture (v Normal Pasture)	-0.00110	-0.00133	-0.000750				-0.000943	-0.00188	-0.000912
	(0.00118)	(0.00199)	(0.00142)				(0.00118)	(0.00198)	(0.00135)
Bad Pasture Previous Season				-0.00105	-0.00167	-0.000955	-0.000497	0.000195	-0.00120
				(0.00147)	(0.00264)	(0.00184)	(0.00140)	(0.00257)	(0.00175)
Good Pasture Previous Season				0.00335**	0.00856***	-0.00410***	0.00430***	0.0101***	-0.00350**
				(0.00152)	(0.00271)	(0.00145)	(0.00153)	(0.00258)	(0.00141)
N	24752	12015	12737	25582	12825	12757	24752	12015	12737
Mean	0.00554	0.00765	0.00362	0.00610	0.00715	0.00499	0.00549	0.00630	0.00474
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Seasons	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bitemporal							✓	✓	✓

Notes: This table shows the effect of good pasture quality (>80th percentile of the historical NDVI z-score per season per region) and bad (<20th percentile) pasture quality per season and region on the propensity to be raided, compared to normal pasture quality (between the 20th and 80th percentile). This is estimated for the concurrent season in Columns 1-3 (Equation 2, for the previous season only (Columns 4-6) and for both the concurrent and previous season jointly in Columns 7-9 (Equation 3). Estimates are from household fixed effects regressions for all seasons (Columns 1, 4 and 7), rainy seasons only (columns 2, 5 and 8, and dry seasons only (columns 3, 6 and 9). Season fixed effects are included. Standard errors are in parentheses, bootstrapped with 1000 iterations. Control variables included: Number of household members, Household head school attendance, total TLU owned (winsorized at 99 percent), share of camels in owned TLU, share of cattle in owned TLU, share of goats and sheep in owned TLU. The number of observations is slightly higher in the columns that only include pasture shocks of the previous season, as an additional observation of pasture quality can be included. Significance denoted by stars: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Based on prior qualitative evidence (Witsenburg and Adano, 2014) we speculate that this may be the case because the health of animals will not have deteriorated as much as during normal or bad pasture dry seasons, increasing the return of raiding. In dry seasons, however, we observe a contradictory effect: prior rainy seasons with good pasture *decrease* the propensity to be raided in a dry season. We observe a 0.4 percentage points decrease in the likelihood of losses due to raiding, significant at the 1% level, compared to a 0.499% likelihood during dry seasons after a normal pasture rainy season, an 82% decrease. Columns 7-9 show the estimates with both concurrent and lagged pasture quality estimated jointly, as per Equation 3. The control mean is the propensity to be raided during a normal pasture season with a preceding normal pasture season. The joint estimation does not change the estimated effects in Columns 1-6.

5.1.1 Robustness

We perform various robustness tests. First, we show that our results are robust to clustering standard errors at the household level (Table 9) or sublocation/kebele level (Table 8) as opposed to bootstrapping standard errors, which we do in our main regressions. We also show our results are robust to the exclusion of control variables (Table 10) and to excluding control variables and seasonal fixed effects (Table 11). Table 12 and Table 13 show the results estimated in Table 2 (with 20% and 80% cut-offs for bad and good pasture respectively), but with different thresholds for the cut-off between normal and bad pasture and normal and good pasture. Table 12 sets the cut-off for bad pasture at 25% of the average NDVI z-score for that region in that specific season and above 75% for good pasture. In Table 13, we set the cut-off for bad pasture at 15% and for good pasture at 85%. Results are all qualitatively similar, but concurrent bad pasture consistently increases conflict in the dry season, with a slightly smaller effect than in Table 2 for the 25% threshold and a slightly larger effect than in Table 2 for the 15% threshold. This suggests that the more extreme the negative shock to pasture quality is, the larger the likelihood of experiencing losses from raiding. The effects of previous season good pasture quality, however, are similar for the 15% threshold, but change in sign for the 25% threshold, suggesting that the increase in pasture quality needs to be significant for it to increase incentives to raid significantly, for it to increase the likelihood of losses due to raiding.

We believe that defining pasture quality at the regional level (Division/Woreda level) is the correct geographical aggregation level, because this area captures the area where livestock herds, namely beyond the boundaries of the kebele/sublocation. We do, however, also show results when we aggregate pasture quality at the villagelevel (Kebele/Sublocation) (Table 14 in the Appendix). Results for negative shocks to pasture quality (bad pasture) remain qualitatively similar. Positive shocks to pasture quality in good seasons (good pasture), however, has a negative effect on the likelihood to be raided in all seasons, concurrent and lagged. We suspect this is because animal raiding in good seasons is more likely to happen much further away from basecamps, which are defined by the kebele/sublocation. After all, the health of the animals during these seasons is better, making them more able to move over large distances.

5.2 Insurance, Pasture Quality and Livestock Losses

Table 3 shows the effects of insurance coverage and indemnity payments on losses from raiding as per Equation 5 and Equation 6. Column 1 in Table 3 shows the overall local average treatment effect (LATE) of the household being insured, for all seasons. It shows that if a households is insured, irrespective of whether they have received indemnity payments or not, this reduces the likelihood of being raided by 1.995 percentage points. This corresponds to an intent-to-treat effect (ITT) at the population level of 0.87 percentage points, relative to a control mean of 0.77 percentage points. Columns 2 and 3 show the results for dry and rainy seasons, respectively, showing that – while the effect is significant for rainy seasons – the effects in rainy seasons are not significantly different from the effects in dry seasons. Columns 4 and 5 show the effects of the insurance index being triggered in an index unit, during the dry season in Column 4, and during the subsequent rainy season during Column 5. Consistent with the effects observed for bad pasture, we see that a triggered index increases losses from raiding in both the dry and rainy seasons. Columns 6 and 7 show the interaction effects for insurance coverage and the index trigger, and the rows "Coef: $(\gamma 1 + \gamma 2)$" and "p-value: $(\gamma 1 + \gamma 2)$" show the coefficient and p-value of the combined effect, which we think of as a the LATE of indemnity payments. Column 6 shows that indemnity payments, and not insurance coverage, significantly reduce the likelihood that households lose livestock due to raiding during dry seasons, by 8.9 percentage points, significant at the 1% level, corresponding to a 0.27 percentage point ITT, compared to a mean of 0.47%, implying a 57 % reduction in the likelihood to be raided. We observe no effects of indemnity payments being triggered on subsequent rainy seasons, as per Column 7, while the reduction due to insurance coverage remains.

Table 3: The Effect of Insurance Coverage and Indemnity Payments on Losing Livestock due to Raids

	All	Dry	Rainy	Dry	Rainy	Dry	Rainy
	Loss due to Raids	Loss due to Raids	Loss due to Raids	Loss due to Raids	Loss due to Raids	Loss due to Raids	Loss due to Raids
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Predicted Insurance ($\gamma 1$)	-0.019954***	-0.016485	-0.021247**			0.003403	-0.035108*
	(0.006153)	(0.010174)	(0.010249)			(0.010070)	(0.020454)
Index triggered				0.008105***	0.004559*	0.010937***	0.001771
				(0.002020)	(0.002549)	(0.002672)	(0.003093)
Pred. ins. x index triggered ($\gamma 2$)						-0.092249***	0.050356
						(0.035464)	(0.037220)
Coef: ($\gamma 1 + \gamma 2$)						-0.088846	0.015248
p-value: ($\gamma 1 + \gamma 2$)						*0.010929*	*0.661148*
Household f.e.'s	✓	✓	✓	✓	✓	✓	✓
Season controls	✓	✓	✓	✓	✓	✓	✓
Control Mean Losses due to Raid	0.006777	0.004682	0.008895	0.004682	0.008743	0.004682	0.008743
Observations	28477	14311	14166	14310	9265	14310	9265

Notes: The table presents estimated Local Average Treatment Effects (LATE) of the *predicted* insurance and the *predicted* receipt of indemnity payments. Insurance is instrumented by having received a discount coupon valid for the season. Indemnity payments are the interaction between insurance and the index being triggered in that season or the prior season. Household and seasonal fixed effects are included. Column 1 presents the estimation for all seasons, columns 2, 4 and 6 present estimations in dry seasons, and columns 3, 5 and 7 for rainy seasons. Standard errors are bootstrapped (1000 iterations). Standard errors in parentheses. Significance denoted by stars: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The row labeled "Coef: ($\gamma 1 + \gamma 2$)" displays the effect of indemnity payments, constructed by adding up the marginal effects of predicted insurance and its interaction with the index trigger. The row below labeled "*p-value*: ($\gamma 1 + \gamma 2$)" show the statistical significant of this effect.

Given that our focus in this paper is on negative and positive shocks leading to, respectively, resource scarcity and resource abundance, Table 4 presents interactions of insurance coverage and the indemnity payment with pasture shocks, as per Equation 7. Columns 1 and 2 provide the effects of insurance, irrespective of indemnity payments, interacted with good and bad pasture shocks. In Column 1, the rows titled "Coef: $\gamma 1 + \gamma 4$" and "p-value: $\gamma 1 + \gamma 4$" show the combined effect of being insured while experiencing a bad pasture shock during a dry season. While we do not observe a significant interaction, we observe a significant reduction in the likelihood of losses due to raiding of 5.5 percentage points (p-value 0.04). Although bad pasture usually increases the likelihood of losses due to raiding in the dry season, insurance more than offsets that increase. This is consistent with the general reduction in the likelihood of losses we observe during all dry seasons, as presented in Table 3. In Column 2, the rows titled "Coef: $\gamma 1+\gamma 3$" and "p-value: $\gamma 1+\gamma 3$" show the combined effect of being insured while experiencing a good pasture shock during a rainy season. We observe a significant interaction, and the combined effect suggests that insurance during good pasture shocks in rainy seasons increases the likelihood of raiding by 5 percentage points (p-value 0.015). This corresponds to an ITT of 0.0036, representing a 46.6% increase in the likelihood to be raided compared to the control mean of 0.0077. Columns 3 and 4 add the interaction between insurance and the index trigger, to add the effect of indemnity payments. These results should be interpreted with caution, as bad pasture shocks and the index trigger are correlated, potentially leading to multicollinearity - although the correlation is imperfect at 0.39, significant at the 1% level. Column 3 shows that none of the interactions are close to significance, but the general effect of indemnity payments on the likelihood of losses during dry seasons – that we observed in Table 3 – becomes stronger during bad pasture shocks ("Coef: $\gamma 1 + \gamma 2 + \gamma + \gamma 5$" and "p-value: $\gamma 1 + \gamma 2 + \gamma + \gamma 5$") at 14.7 percentage points (p-value 0.007). This translates to an ITT of 0.00399, an almost complete reduction of the control mean 0.004688. The aggravating effect of insurance coverage during positive shocks to pasture in rainy seasons becomes marginally insignificant in Column 4 (p-value 0.135), but there is no significant combined effect, likely due to lack of statistical power. [18]

[18] For robustness, Table 15 in the Appendix shows these results with the pasture of last season, rather than its concurrent effects (the marginal effects of insurance are not significant, but the main patterns are copied and the good pasture in the previous season confirms the relationships as found in Table 2).

Table 4: Insurance Coverage, Insurance Indemnity payments s, Pasture Quality and Livestock Losses

	Dry Loss due to Raids (1)	Rainy Loss due to Raids (2)	Dry Loss due to Raids (3)	Rainy Loss due to Raids (4)
Predicted Insurance ($\gamma 1$)	-0.006065	-0.022613**	0.004859	-0.031628
	(0.011141)	(0.010080)	(0.010661)	(0.023353)
Pred. ins. x index triggered ($\gamma 2$)			-0.002452	0.033209
			(0.065201)	(0.024597)
Index triggered			0.008181**	-0.008041
			(0.003650)	(0.005030)
Good Pasture (v Normal Pasture)	-0.000822	-0.005963***	0.000513	0.000823
	(0.001563)	(0.001850)	(0.001554)	(0.004284)
Bad Pasture (v Normal Pasture)	0.005544**	0.003257	-0.000990	0.000219
	(0.002530)	(0.002994)	(0.002881)	(0.005261)
Good Pasture x pred. ins. ($\gamma 3$)	0.009179	0.072501***	0.000536	0.043962
	(0.025154)	(0.021183)	(0.024822)	(0.030901)
Bad Pasture x pred. ins. ($\gamma 4$)	-0.048580	-0.007531	0.014073	-0.020395
	(0.030609)	(0.046057)	(0.026416)	(0.066634)
Good Pasture x pred. ins. x index triggered ($\gamma 5$)			0.000000	-0.068313
				(0.114131)
Bad Pasture x pred. ins. x index triggered ($\gamma 6$)			-0.164117	0.108848
			(0.102813)	(0.116814)
Coef: $\gamma 1 + \gamma 2$			0.002407	0.001581
p-value $\gamma 1 + \gamma 2$			*0.970929*	*0.893595*
Coef: $\gamma 1 + \gamma 3$	0.003114	0.049887	0.005395	0.012334
p-value $\gamma 1 + \gamma 3$	*0.897780*	*0.015307*	*0.823466*	*0.625069*
Coef: $\gamma 1 + \gamma 4$	-0.054645	-0.030144	0.018932	-0.052023
p-value $\gamma 1 + \gamma 4$	*0.042043*	*0.502640*	*0.445127*	*0.445127*
Coef: $\gamma 1 + \gamma 2 + \gamma 3 + \gamma 5$			0.002943	-0.022770
p-value $\gamma 1 + \gamma 2 + \gamma 3 + \gamma 5$			*0.966274*	*0.837658*
Coef: $\gamma 1 + \gamma 2 + \gamma 4 + \gamma 6$			-0.147637	0.090034
p-value $\gamma 1 + \gamma 2 + \gamma 4 + \gamma 6$			*0.006743*	*0.357658*
Household f.e.'s	✓	✓	✓	✓
Season controls	✓	✓	✓	✓
Control Mean Losses due to Raid	0.004688	0.007674	0.004688	0.008745
Observations	14291	13291	14291	9262

Notes: The table presents estimated Local Average Treatment Effects (LATE) of pasture quality, any insurance purchase and the *predicted* receipt of indemnity payments, instrumented by having received a discount coupon valid for this period and its interaction with the exogenous triggering of the index. Household and seasonal fixed effects are included. Standard errors are bootstrapped (1000 times). The row labeled Coef: $\gamma 1 + \gamma 2$ displays the effects of the indemnity payments , built from the predicted insurance and the predicted insurance times the index triggered. The row Coef: $\gamma 1 + \gamma 3$ displays the effect of insurance coverage in good pasture seasons, and $\gamma 1 + \gamma 4$ during bad pasture seasons. The row with Coef: $\gamma 1 + \gamma 2 + \gamma 3 + \gamma 5$ shows the effect of receiving an indemnity payment during a good pasture season (note that this is a null effect during the dry seasons, as this combination does not exist). The row $\gamma 1 + \gamma 2 + \gamma 4 + \gamma 6$ show the effects of receiving an indemnity payments during a bad pasture season. The rows below these coefficients labeled *p-value* show its statistical significance. Standard errors in parentheses. Significance denoted by stars: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6 Conclusion and discussion

This paper provides novel evidence of the effect of resource variability on conflict in the same households over time. This paper reveals a dual role of resource fluctuations: negative shocks that lead to pasture scarcity increase conflict during dry seasons, while positive shocks that lead to pasture abundance heighten conflict in subsequent rainy seasons. Previous work, which typically analyses conflict over longer time periods, may therefore have obscured these heterogeneous effects and inaccurately concluded that observed conflicts are caused by resource scarcity or resource abundance, rejecting the alternative.

The positive effect of shocks leading to pasture scarcity on concurrent conflict is consistent with the resource scarcity theory. This suggests that during droughts, herders adopt riskier mitigation strategies. For instance, herders may migrate further from base camps or into contested areas to secure sufficient pasture for herd survival (Bannon and Collier, 2003; Von Uexkull et al., 2016; Hidalgo et al., 2010; Sakketa et al., 2024; Gehring and Schaudt, 2024). These tactics, while aimed at avoiding starvation, also increase vulnerability to raids. Furthermore, these results align with a broader literature that links decreased rainfall to increased conflict, and are consistent with findings that increased temperatures and climate shocks in particular correlate with reduced vegetation in the region (Burke et al., 2015, 2024; McGuirk and Nunn, 2024; Eberle et al., 2023; Hsiang et al., 2011; Von Uexkull and Buhaug, 2021). The *ex-post* effects of insurance show that when the impacts of droughts are mitigated using a policy intervention, the propensity to be raided significantly decreases. This can also be ascribed to the removed necessity for risky mitigation strategies. Good pasture in the rainy season preceding a dry season, even when controlling for current pasture, significantly decreases the propensity to be raided. A rainy season with abundant pasture provision arguably creates good herd (or other forms of financial) health, removing the necessity for risky mitigation strategies during the dry seasons (Witsenburg and Adano, 2014). In conclusion, we see a necessity-based conflict argument in the dry season, when scarcity is at its harshest.

However, the necessity-driven dynamics in dry seasons alone do not fully explain the observed conflict outcomes. Relatively good pasture during a dry season *increases* the propensity to be raided in the subsequent rainy season, an effect which persists and even increases in magnitude when controlling for concurrent (rainy) season pasture conditions. This may be explained by a lack of deterioration of herd health and infrastructure during pasture abundant dry seasons, increasing the returns to raiding in subsequent rainy seasons. Scoones (2023) and Witsenburg and Adano (2014) provide qualitative evidence for this relationship. Even during normal dry seasons, pasture can be quite scarce (see Figure 1 and Figure 2). Although bad pasture dry seasons (droughts) trigger risky mitigation strategies compared to normal pasture dry seasons, normal pasture dry seasons can be expected to contribute to these deteriorating herd and infrastructure conditions, whereas good pasture might prevent this. These stronger herds and improved infrastructure enhance the return on raiding efforts in the subsequent rainy season. This is noteworthy, as the majority of raiding happens during the rainy seasons. Conversely, if animals are weakened during a normal or bad pasture quality dry season, animal transport becomes comparatively more difficult, increasing the costs of raiding.

Like the impacts of resource shocks, the impact of insurance is also heterogeneous, depending on timing and pasture conditions. During dry seasons, the effect of insurance on conflict is entirely driven by indemnity payments, while during rainy seasons the effect is driven by insurance coverage, both reducing losses from raiding. During bad pasture shocks, the effects of indemnity payments are even stronger. This clearly stresses the mitigating role of indemnity payments in preventing resource-scarcity driven conflict. We, however, also find that the effect of insurance during positive pasture shocks in rainy seasons is orthogonal to the effect during normal and bad pasture rainy seasons: While insurance coverage generally reduces the likelihood of losses due to conflict in rainy seasons, insurance coverage *increases* this likelihood during positive pasture shocks, which we suggestively attribute to the potential behavioral effects of *ex ante* insurance coverage, incentivizing higher-risk but higher-return strategies.

A limitation of the analyses in this paper is that we rely on one conflict outcome "losses due to being raided". We know from the extensive conflict module, which we implemented as part of the 2020 survey, that there is much more conflict occurring in this population than is captured by the variable we use. What works in our favor is that questions about being victims of conflict rather than perpetrators of conflict are more reliable, but triangulation of our data is still important. Finally, since these mechanisms rely on herd movement, long-term data on livestock migration and campsite selection would offer valuable insights into how these dynamics influence and are influenced by pasture and conflict risk.

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7 Appendix

7.1 Literature Reviews

7.1.1 Climate, Resources and Conflict

The link between climate and conflict has been prominent in the traditions of political economy, political science, geography, psychology and history. These spotlight the importance of weather shocks in causing conflict, violence, political instability or even collapse of civilizations (Burke et al. (2015)). El niño, for example, as a rare extreme shift in climate, was shown to increase civil conflict in Hsiang et al. (2011) as the first causal study on climate and conflict. The most convincing arguments hinge on the shift in availability of natural resources, uprooting livelihood strategies as well as presenting opportunities for altered or strengthened power dynamics.

The interest in the field of quantitative economics is relatively new, but has surged over the past years, enabled by improved data availability. However, these studies use data which is predominantly if not exclusively on a high aggregation level, with this study presenting household-level data, a clear gap in the literature and opening new pathways for research into the causal mechanisms (Burke et al. (2015)). In 2015, Burke et al. (2015) presented a comprehensive meta analysis of quantitative literature. They conclude that a one standard deviation increase in temperature increases interpersonal conflict by 2.4% and intergroup conflict by 11.3 %. They emphasize the need for increased knowledge of the mechanisms. How climate change impacts resource supplies, particularly through rainfall, varies by region. In East Africa, more (sequential) droughts are observed. In West Sub Sahara Africa, however, more and excessive rainfall is observed. In all regions, the resource supply and rainfall are less predictable and move more towards the extremes. This in itself alters economic behavior through changing risk estimations. Climatic insecurity and extremes change behavior and social interactions, in turn affecting the likelihoods of conflicts of all types to arise. It hence does not impact conflict immediately: its impact is the change in conditions which *can* cause conflict. Hence, to substantially speak to the link between climate and conflict, these intermediate behavioral changes need to be understood and studied. In Burke et al. (2024), the authors provide an update with a new meta-analysis. Although they note the found effects are smaller than in earlier analyses, the results are still statistically significant, providing additional support for weather variability leading to conflict. Several "lessons" for causal mechanisms are proposed. Firstly, the importance of dependence on agriculture to the effect of climate on conflict. The most convincing behavioral channels are logically present in circumstances where weather has a large impact on the livelihoods of the people involved in potential conflict. This is supported by agricultural prices and real wages seem to cause a similar effect on conflict. The behavioral mechanisms proposed in this paper are in line with this idea, seeing that both the necessity to take risks (scarcity) and opportunity costs of conflict (abundance) are only logical when a person's main livelihood and tasks are dictated by the changes in pasture. Secondly, they find that the effects of these shocks on conflict are mitigated by political and economic institutions. These shape the coping strategies (including those suggested in this paper) and hence the effect of climate on conflict. Thirdly, migration and movement are a key factor in coping strategies across their reviewed papers, with institutions in both the beginning and end locations impacting the risk of conflict. Migration and transportation costs are hence a key factor. Our population is by definition exceptionally mobile, and this paper suggests the "cost" involved is the propensity to be raided, an exceptionally direct example of this link. Fourthly, policies that reduce income and volatility can mitigate these effects. This is what we find for IBLI as well, particularly *ex post* - with well-timed payments at times at which income drops drastically, smoothening income. Finally, psychological and physiological channels should not be disregarded, and can have an impact regardless of economic channels. Note that although the averages of all studied papers lead to a positive impact, there are also studies in their review that find significant *decreases* in conflict with higher climate variability, or results without statistical significance (even with the publication bias towards significant results). This is especially when looking at impacts on civil war (e.g., Landis (2014); Guardado and Pennings (2020); Miguel et al. (2004)).

Natural resources are not a monolith. This study deals with pasture, which together with other typically communal and renewable resources is directly impacted by rainfall and other elements. In monetary terms, these are often of lower value and have hence a substantially different behavioral effect than higher valued resources such as minerals and oil, which are not impacted by rainfall as directly and are non-renewable. A majority of the literature focuses on the latter category. These are the pillars of political theories such as the (conditional) resource curse, and have wide effects on power dynamics and political systems (Sachs and Warner (2001)). Oil, for example, is shown to negatively impact democracy, increase corruption and increase violent conflicts — but this is highly conditional on the institutional structures in place (see e.g. Ross (2015), Le Billon (2010) & Ahmadov (2014)). Resource abundance in these contexts is often defined by availability, but overlooks selective accessibility Welsch (2008)). Ross (2004) has laid the foundation for differential resource analyses, arguing that oil increases civil war, minerals do not cause but might extend conflicts, and shocks in *legal* agricultural commodities do not cause civil war. This last point is now threatened by recent data-driven research, including this paper, as can be seen in Burke et al. (2015), although these include a broader definition of both agricultural commodities and conflict than in Ross' analysis. This literature review will focus predominantly on agricultural commodities and analyses proxying resource availability by rain and pasture levels, seeing the topic and claims of this study.

However, cannot translate increased rainfall, for example, to increased resources directly, as is occassionally done. Nuance and conditionality are required here. Crost et al. (2018) analyze conflict-related incidents in the Philippines to understand how seasonal rainfall variations affect agricultural production and civil conflict. They find that increased dry-season rainfall enhances agricultural output and reduces conflict intensity, whereas wet-season rainfall harms crops and escalates conflict. Hence, rainfall leads to an increase in resources (and conflict) in dry seasons, and diminishing resources in rainy seasons. Therefore, our analysis based on pasture rather than rainfall and disaggregated by (type of) season is well positioned to capture similar tendencies in pastoral settings.

7.1.2 Resource Scarcity

Research highlights how resource scarcity, particularly of renewable resources like water, land, and food, can exacerbate conflicts, especially in regions vulnerable to climate change and governance issues. Resource scarcity can strain local populations, leading to competition over diminishing supplies, which, in turn, triggers social unrest and (violent) conflict. Bannon and Collier (2003) argue that competition over scarce resources often exacerbates tensions between groups, leading to prolonged conflicts. This is particularly evident in regions where resources are limited but highly sought after. It highlights how disparities in resource distribution can fuel grievances and create social unrest. When certain groups perceive themselves as marginalized or disadvantaged in resource access, it can lead to increased conflict and instability.

Whether this causes conflict depends highly on the institutional structure (See also Homer-Dixon (1994) & Hidalgo et al. (2010)). This ties into the framework as laid out by North (1990), where the stability of regimes and eruption of conflict is argued to depend on the formal and informal institutions that have evolved.

Water scarcity linked to climate variability, for example, has been shown to contribute to armed conflicts. In such cases, diminishing water resources, aggravated by poor governance and inadequate adaptation policies, increase the likelihood of violence among competing groups. This is particularly visible in conflict zones, where communities already face poverty and instability ((Regan and Kim, 2020), (Ide, 2020)). A vicious cycle of conflict, or "conflict trap", can therefore be expected. These studies are, however, all on a grid, aggregate level basis and emphasize the need for increased insight into the causal mechanisms. Von Uexkull et al. (2016) show that droughts during growing seasons increase the likelihood of conflict for agriculturally dependent or politically marginalized groups. They argue that drought and conflict have a reciprocal relationship, increasing vulnerability in a vicious cycle. This is supported by Buhaug and Von Uexkull (2021). The larger the group's dependence on renewable resources, the higher the probability drought causes conflict. Pastoralists are highly dependent on renewable resources, as their livestock is largely sustained by communal pasture and water. This finding particularly worrying seeing that droughts in these East African pastoral areas can be expected to increase due to climate change. Nandintsetseg et al. (2024) model in Eurasia rangeland productivity will decrease this century and put significant pressure on pastoral systems as a whole, using a risk approach based on catastrophic droughts. Boone et al. (2024) show that with recent weather trends, a sharp decrease in TLU accommodation in Northern Kenya is expected. This underlines the increased pressure on the land and consequent competition over pasture and water. Mobility and displacement are often suggested as intermediate variables in this relationship. When resources become scarce communities that are most affected often resort to migration as an adaptation strategy. This displacement, however, can exacerbate existing tensions or create new conflicts in both the areas they leave and the places they move to. In regions of Sub-Saharan Africa, migration triggered by drought or agricultural failure can increase competition for resources like land, leading to tensions between local communities and incoming migrants. This is often argued, for example in an essay by Kim and Garcia (2023), but, to the best of our knowledge, has not been proven causally. Ouma et al. (2011) show that migration is one of the risk mitigation strategies, although not the most prominent one reported at 20%. They attribute its decreasing significance to the increased difficulty of migration. Still, this requires little coordination compared to the community action that is surveyed to be the most promising and is possible in all areas unlike the sedentary agriculture and livelihood diversification surveyed as alternative risk mitigation strategies. Therefore, when pushed, migration might be the most viable short term option. More importantly, non-migratory movement is highlighted as an essential risk mitigation strategy. This includes the dry season migration into raiding-prone areas we discuss. The unrest and competition over land that follow mimic those of larger scale migration. Hidalgo et al. (2010) instruments economic scarcity by rainfall and shows that this causes encroachment by rural poor of large landholders in Brazil, leading to conflicts. This is highly dependent on the Division of land and equality in land ownership and land tenure systems. In our analysis, as well, we predict increased movement due to scarce pasture, particularly during dry seasons, when the cattle is away from the base camp. To sustain the herd, herders need to migrate further — and likely closer to opposing groups — or into contested areas. This risky mitigation strategy becomes required, but increases chances of conflict. Tache and Oba (2009) discuss inter ethnic pastoral conflicts in Southern Ethiopia, which they find largely at the borders of grazing lands. This supports the notion of pushed boundaries in search of viable pasture causing conflict, and scarce pasture necessitates additional strategies to search for pasture.

In brief, droughts necessitate risky mitigation strategies pushing groups of pastoralists together. Grievances between these groups due to the increased competition exacerbate raiding and conflict.

7.1.3 Resource abundance

Resource abundance leading to conflict is most extensively studied in the context of the resource curse. This is expanded on above and generally focuses on centralized materials with high monetary value inciting or funding conflicts, competition and authoritarian systems more fruitful for conflict. This paper considers pasture. This the type of natural resource typically publicly available to some extent (a commons), lower in monetary value and highly dependent on climatic conditions.

Inequality, grievances and other motives are not sufficiently explanatory for conflict, Collier and Hoeffler (2004) argue: it needs to be viable as well. A second argument therefore considers opportunity costs of conflict. Theories of resource abundance suggest that during periods of abundance, the opportunity cost of time of individuals potentially involved in conflict is lower, and therefore incentives to engage in conflict may be increased. Collier and Hoeffler (2004) base their conclusions on an econometric model predicting the outbreak of civil conflict based on motive and opportunity using data of 750 five-year episodes from 1960 to 1999. Harari and La Ferrara (2018) conclude that opportunity costs are the most convincing channels through which local weather shocks increase rebel recruitment. This is particularly convincing for labor intensive livelihood activities, where time investment has higher livelihood returns and hence time invested in conflict is at the expense of income to a higher extent (Dal Bó and Dal Bó (2011)). Logically, these effects are higher if the weather impacts the income for the group that would fight. Pastoralism is a labor intensive endeavor carried out by the same age set of young men that are the predominant fighters in the community. With good pasture, less effort is required to sustain the herd as smaller distances need to be covered to sustain the herd. Hence, the marginal benefit from labor decreases with good pasture, and the opportunity costs of conflict decrease. Therefore, good pasture provides the conditions in which more time invested in conflict is accommodated.

On top of this argument around opportunity costs, resource abundance also creates the opportunity to raid in more simple terms. Extensive resource scarcity, especially droughts, inhibits raiding due to animal health and ample water and pasture. In the drylands, this can be extended to normal seasons rather than droughts, but is most compelling in periods of abundant pasture. Abundant pasture makes raiding easier. Witsenburg and Adano (2014) argue that during rainy seasons raids are more violent and frequent, supporting the opportunistic side to raiding.

Another argument arguing for raids during periods of abundance emphasizes the increased cooperation between groups during periods of scarcity. During extreme drought conditions, pastoralist communities often adopt mutual aid strategies such as sharing scarce water resources, pooling livestock, and engaging in collective mobility to areas with better grazing opportunities. These cooperative mechanisms are vital for reducing vulnerability and increasing resilience. For example, Witsenburg and Adano (2014) show that pastoralists in Kenya and Ethiopia frequently engage in "reciprocal grazing agreements," allowing different groups to access each other's lands during drought periods. These arrangements not only facilitate survival but also reinforce social ties between groups. Additionally, in Tanzania, communal resource-sharing practices, such as the Maasai *olopololi* (grazing reserves), help mitigate the impacts of environmental stress. Such cooperation is crucial for long-term sustainability, helping to maintain the delicate balance between competition and survival in an increasingly climate-impacted region. In reverse, periods of abundance, where groups do not need each other, do not have this cooperation and therefore create an opportunity for conflict. Adano et al. (2012) link wetter years to increased conflict in Marsabit, reiterating that the informal institutions developed to deal with climate shocks are dependent on intergroup collaboration and the ceasing of conflict. This argument is strengthened by Schrieks et al. (2024). They show that scarce pasture conditions are shown to increase risk-averse behavior by pastoralists in a framed field experiment. Although some level of risky mitigation strategies might still be required during periods of drought, as described above, this means that in the absence of droughts people might engage in more risky behavior such as livestock raiding.

7.2 Mechanisms: IBLI to conflict

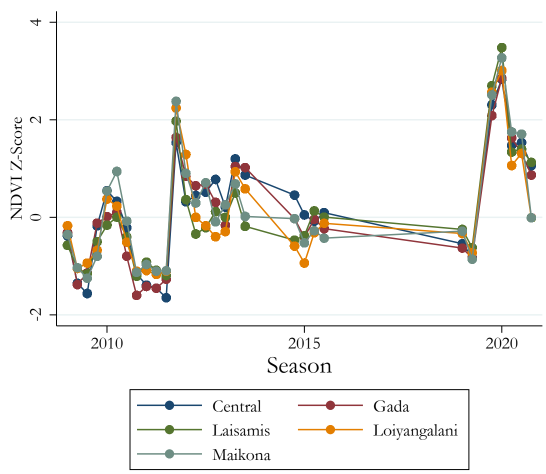
IBLI decreases conflict through a reduced need to adopt risky mitigation strategies during droughts. Firstly, *ex post* indemnity payments, if provided in a timely manner, may enable pastoral households to purchase water and fodder, and make other investments in their herd (Jensen et al., 2017). This allows them to keep their livestock alive without resorting to risky mitigation strategies that increase the likelihood of being raided. For instance, migration into contested territory is a high-risk strategy, and qualitative research (Taye, 2023) indicates that households with IBLI migrate less during droughts than those without IBLI in Dire and Gomole, Ethiopia. Secondly, IBLI facilitates livelihood diversification, either through the expansion of non-agricultural income sources that help absorb shocks or through the adoption of drought-resistant agricultural practices (Mobarak and Rosenzweig, 2012; Cole et al., 2017). With IBLI reducing the need for households to maintain a financial buffer to absorb shocks, additional resources can be allocated to *ex ante* diversification. *Ex post*, indemnity payments can be used to further diversify livelihoods or prevent the depletion of savings due to droughts. Finally, the presence of IBLI among other households may *ex post* reduce incentives to restock herds through raids, especially if herds were preserved during droughts. This could lower overall conflict rates and reduce the likelihood of being raided. Moreover, if households with IBLI no longer need to engage in raids to replenish their herds, the provocation of counter-raids is also minimized, thereby reducing their propensity to be raided.

IBLI increases conflict through the increased productivity hypothesis and wealth effects. By reducing the economic risks associated with livestock rearing, IBLI enables herders to increases the production per TLU per month, as well as reduces livestock losses (Jensen et al., 2017). This increases the value of TLU and the attractiveness to steal these, both *ex ante* and through the reinforcing effects of *ex post* indemnity payments. Additionally, if IBLI enhances the overall wealth of pastoralists (Jensen et al., 2017), their relative risk aversion may decrease (Heinemann, 2008). Consequently, pastoralists could exhibit behavior that makes them more vulnerable to being raided. However, this reduction in risk aversion may not extend to situations involving bodily harm and other non-economic decision-making (Paulsen et al., 2012).

IBLI increases conflict through crowding out informal networks. Risks to livelihoods are often shared through informal social networks. However, formal insurance, such as IBLI, is known to *ex ante* crowd out these informal insurance mechanisms (Cecchi et al., 2016). When communities no longer rely on one another to spread risk, the cost of social upheaval in the form of conflict may decrease. Nevertheless, informal networks are generally better suited for addressing idiosyncratic risks rather than covariate risks like droughts. This raises questions about the applicability of this argument in the context of index insurance (Takahashi et al., 2019).

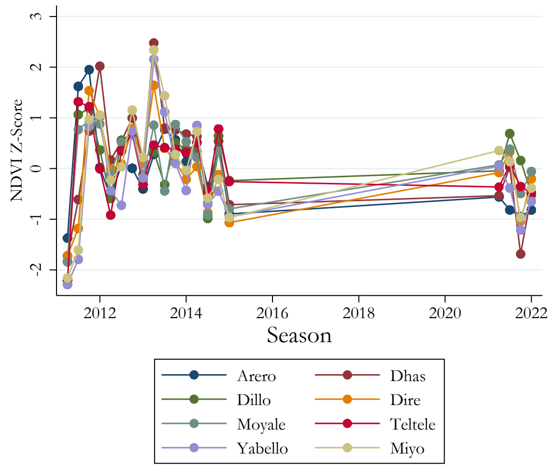
7.3 Figures and Tables

Figure 5: NDVI Z-Score per Season by Division



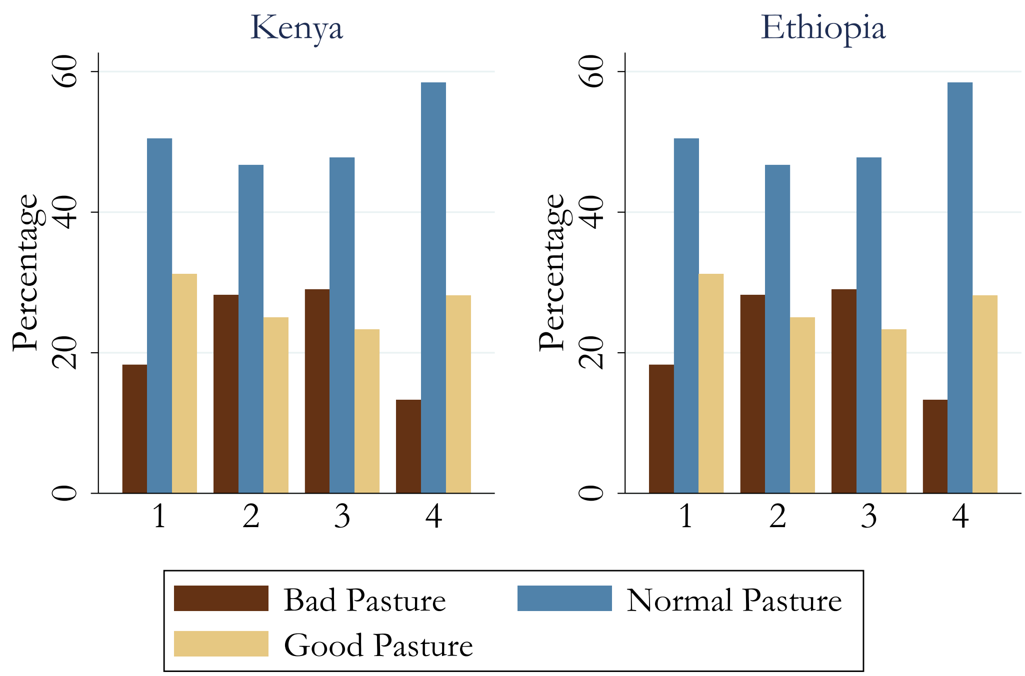
This figure presents the NDVI z-scores per season for each Division. These z-scores are calculated from raw NDVI data by season and location, so they present deviations from the average pasture provision. This figure shows the extent to which the pasture availability of the Divisions, across different seasons move in tandem., compared to the historical distribution for each Division. The seasonal scores are provided for all seasons that are matched to the household panel, so the gap is explained by the gap in data collection rounds.

Figure 6: NDVI Z-Score per Season by Woreda



This figure presents the NDVI z-scores per season for each Woreda. These z-scores are calculated from raw NDVI data by season and location, so they present deviations from the average pasture provision. This figure shows the extent to which the pasture availability of the Woredas, across different seasons fluctuate in tandem., compared to the historical distribution for each Woreda. The seasonal scores are provided for all seasons matched that are to the household panel, so the gap is explained by the gap in data collection rounds.

Figure 7: Pasture Quality Categories, by Season



Notes: This graph presents the percentage of seasons per country with an NDVI z-score indicating good, normal, and bad pasture quality. This quality is defined by region and month. If the NDVI z-score is the 20th percentile or less, the season is demarcated as bad, 80th percentile or over as good, and between the 20th and 80th percentile as normal. This is provided by season, with SD referring to the short dry season, LR to the long rainy season, LD to the long dry season and SR to the short rainy season. This graph only includes the seasons which are matched to the household dataset and hence included in the analysis, explaining why the percentages are not 20%, 60% and 20% for Bad, Normal and Good pasture respectively.

Table 5: Descriptive Table IBLI Panel Data Variables: Kenya

	mean	sd	min	max
No. of household members (discrete)	11.024	6.41	1	30
Male headed household (binary)	0.650	0.48	0	1
Tropical Livestock Units owned (decimal)	24.987	35.98	0	725
Share of cattle in TLU (proportion)	0.262	0.35	0	1
Share of camels in TLU (proportion)	0.315	0.32	0	1
Share of goats/sheep in TLU (proportion)	0.423	0.34	0	1
Moved livestock to sattelite camp in the previous season (binary)	0.736	0.44	0	1
No. of livestock loss events per season (discrete)	1.508	0.84	1	9
No. of livestock loss events due to starvation or droughts per season (discrete)	0.646	0.87	0	7
No. of livestock loss events due to rain per season (discrete)	0.056	0.25	0	3
No. of livestock loss events due to raiding/rustling/conflicts per season (discrete)	0.022	0.17	0	3
No. of livestock loss events at the satellite camp per season (discrete)	0.311	0.62	0	7
IBLI coverage this season (binary)	0.051	0.22	0	1
IBLI payout received this or in the previous season (binary)	0.045	0.21	0	1
Lost animals due to raiding in a rainy season (binary)	0.010	0.10	0	1
Lost animals due to raiding in a dry season (binary)	0.005	0.07	0	1
Has ever lost an animal due to raiding (binary)	0.136	0.34	0	1
Observations	24973			

Notes: This table presents the summary statistics for Kenya: the mean, standard deviation, minimum value, maximum value (columns 1-4, respectively) and the number of observations in total (bottom row). These are the averages across the entire IBLI panel, representing 7 rounds in Kenya between 2012 and 2020. They are measured at the annual level unless specified differently. *Has ever lost an animal due to raiding* is 1 if the household has lost an animal due to raiding in any of the survey rounds. All binary variables are 1 if the statement applies and 0 otherwise. The proportional shares of cattle, camels and goats/sheep refer to the animals owned by the household and add up to 1, unless the household does not own any livestock in which case this variable is omitted. All discrete variables required answers with increments of 1. TLU are tropical livestock units, with a cow being 1 TLU, a camel 1.4 TLU and a goat or sheep 0.1 TLU. TLU therefore has increments of 0.1.

Table 6: Descriptive Table IBLI Panel Data Variables: Ethiopia

	mean	sd	min	max
No. of household members (discrete)	7.872	3.06	2	26
Male headed household (binary)	0.810	0.39	0	1
Tropical Livestock Units owned (decimal)	22.759	34.85	0	457
Share of cattle in TLU (proportion)	0.759	0.20	0	1
Share of camels in TLU (proportion)	0.094	0.17	0	1
Share of goats/sheep in TLU (proportion)	0.147	0.15	0	1
Moved livestock to sattelite camp in the previous season (binary)	0.489	0.50	0	1
No. of livestock loss events per season (discrete)	1.460	0.78	1	9
No. of livestock loss events due to starvation or droughts per season (discrete)	0.360	0.66	0	7
No. of livestock loss events due to rain per season (discrete)	0.010	0.11	0	2
No. of livestock loss events due to raiding/rustling/conflicts per season (discrete)	0.001	0.04	0	1
No. of livestock loss events at the satellite camp per season (discrete)	0.235	0.56	0	5
IBLI coverage this season (binary)	0.089	0.28	0	1
IBLI payout received this or in the previous season (binary)	0.008	0.09	0	1
Lost animals due to raiding in a rainy season (binary)	0.002	0.04	0	1
Lost animals due to raiding in a dry season (binary)	0.001	0.03	0	1
Has ever lost an animal due to raiding (binary)	0.017	0.13	0	1
Observations	3512			

Notes: This table presents the summary statistics for Ethiopia: the mean, standard deviation , minimum value, maximum value (columns 1-4, respectively) and the number of observations in total (bottom row). These are the averages across the entire IBLI panel, representing 5 rounds in Ethiopia between 2015 and 2022. They are measured at the annual level unless specified differently. *Has ever lost an animal due to raiding* is 1 if the household has lost an animal due to raiding in any of the survey rounds. All binary variables are 1 if the statement applies and 0 otherwise. The proportional shares of cattle, camels and goats/sheep refer to the animals owned by the household and add up to 1, unless the household does not own any livestock in which case this variable is omitted. All discrete variables required answers with increments of 1. TLU are tropical livestock units, with a cow being 1 TLU, a camel 1.4 TLU and a goat or sheep 0.1 TLU. TLU therefore has increments of 0.1.

Table 7: Timing of IBLI implementations in Kenya & Ethiopia

	Kenya		**Ethiopia**	
Season	**Survey**	**Policy**	**Survey**	**Policy**
SR 2009	Round 1			
SD 2010		Coupon 1		
LR 2010				
LD 2010				
SR 2010	Round 2			
SD 2011		Coupon 2		
LR 2011				
LD 2011		Coupon 3		
SR 2011	Round 3	**Payout 1**		
SD 2012			Round 1	**Payout 2**
LR 2012		Coupon 4		Coupon 1
SR 2012	Round 4			
SD 2013		Coupon 5		Coupon 2
LR 2013			Round 2	
LD 2013		Coupon 6		Coupon 3
SR 2013	Round 5			
SD 2014				Coupon 4
LR 2014		**Payout 3**	Round 3	
LD 2014				Coupon 5
SR 2014		**Payout 4**		**Payout 5**
SD 2015		*Contract Shift*		Coupon 6
LR 2015			Round 4	
LD 2015				*Contract Shift*
SR 2015	Round 6			
LD 2020	Round 7			
SR 2020				
SD 2021				
LR 2021				
LD 2021				
SR 2021				
SD 2022				Round 5

This figure is derived from Barrett et al. (2024). Notes: this figure presents the timeline of the experiment in Kenya and Ethiopia. Round 1 to Round 7 refer to the survey rounds of the IBLI project, in which questions are asked about the last four seasons. Coupon 1 to Coupon 6 refer to the moments at which coupons to receive a discount to the IBLI premium subsidy for the 12-month coverage period were randomly distributed. Payout 1 to Payout 4 are the moments at which indemnity payments made to recipients if the index for their insurance area was triggered. Contract shift refers to the moment when the IBLI contract underwent changes from asset replacement to asset protection.

Table 8: Pasture Condition on the Propensity to be Raided Clustered at Sublocation-Kebele level Concurrently, Lagged and Combined

	All Seasons	Rainy	Dry	All Seasons	Rainy	Dry	All Seasons	Rainy	Dry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Raided	Raided	Raided	Raided	Raided	Raided	Raided	Raided	Raided
Bad Pasture (v Normal Pasture)	0.00383**	0.00392	0.00426**				0.00399**	0.00223	0.00378**
	(0.00186)	(0.00438)	(0.00175)				(0.00177)	(0.00511)	(0.00144)
Good Pasture (v Normal Pasture)	-0.00167	-0.00209	-0.00115				-0.00147	-0.00260	-0.00137
	(0.00261)	(0.00398)	(0.00136)				(0.00251)	(0.00469)	(0.00178)
Bad Pasture Previous Season				-0.000952	-0.00162	-0.000822	-0.000374	0.000146	-0.000975
				(0.00137)	(0.00412)	(0.000936)	(0.000638)	(0.00295)	(0.00120)
Good Pasture Previous Season				0.00360**	0.00923**	-0.00420*	0.00453*	0.0107*	-0.00361
				(0.00174)	(0.00447)	(0.00228)	(0.00240)	(0.00630)	(0.00217)
N	23617	11463	12154	24399	12226	12173	23617	11463	12154
Mean	0.00554	0.00765	0.00362	0.00610	0.00715	0.00499	0.00549	0.00630	0.00474
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Seasons	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bitemporal							✓	✓	✓

Notes: This table shows the effect of good pasture quality (>80th percentile of the historical NDVI z-score per season per region) and bad (<20th percentile) pasture quality per season and region on the propensity to be raided, compared to normal pasture quality (between the 20th and 80th percentile). This is estimated for the concurrent season only (columns 1-3), for the previous season only (columns 4-6) and for both the concurrent and previous season in the same estimation (7-9). It is estimated using a household fixed effects analysis for all season-types pooled (columns 1, 4 and 7), the rainy seasons only (columns 2, 5 and 8, and the dry seasons only (columns 3, 6 and 9). Season fixed effects are included. Standard errors in parentheses, clustered at the Sublocation-Kebele Level. Control variables included: Number of household members, Household head school attendance, total TLU owned (winsorized at 99 percent), share of camels in owned TLU, share of cattle in owned TLU, share of goats and sheep in owned TLU. The number of observations are slightly higher in the columns that only include pasture shocks of the previous season, as an additional observation of pasture quality can be included. Significance denoted by stars: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Pasture Condition on the Propensity to be Raided Clustered at Household level Concurrently, Lagged and Combined

	All Seasons	Rainy	Dry	All Seasons	Rainy	Dry	All Seasons	Rainy	Dry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Raided	Raided	Raided	Raided	Raided	Raided	Raided	Raided	Raided
Bad Pasture (v Normal Pasture)	0.00363**	0.00370	0.00406**				0.00379**	0.00213	0.00364**
	(0.00150)	(0.00253)	(0.00181)				(0.00151)	(0.00250)	(0.00181)
Good Pasture (v Normal Pasture)	-0.00110	-0.00133	-0.000750				-0.000943	-0.00188	-0.000912
	(0.00115)	(0.00190)	(0.00133)				(0.00115)	(0.00188)	(0.00127)
Bad Pasture Previous Season				-0.00105	-0.00167	-0.000955	-0.000497	0.000195	-0.00120
				(0.00142)	(0.00267)	(0.00158)	(0.00137)	(0.00262)	(0.00155)
Good Pasture Previous Season				0.00335**	0.00856***	-0.00410***	0.00430***	0.0101***	-0.00350***
				(0.00149)	(0.00256)	(0.00131)	(0.00146)	(0.00254)	(0.00130)
N	24752	12015	12737	25582	12825	12757	24752	12015	12737
Mean	0.00554	0.00765	0.00362	0.00610	0.00715	0.00499	0.00549	0.00630	0.00474
Controls	✓	✓		✓	✓	✓	✓	✓	✓
Seasons	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bitemporal							✓	✓	✓

Notes: This table shows the effect of exceptionally good pasture quality (>80th percentile of the historical NDVI z-score per season per region) and exceptionally bad (<20th percentile) pasture quality per season and region on the propensity to be raided, compared to normal pasture quality (between the 20th and 80th percentile). This is estimated for the concurrent season only (columns 1-3), for the previous season only (columns 4-6) and for both the concurrent and previous season in the same estimation (7-9). It is estimated using a household fixed effects analysis for all season-types pooled (columns 1, 4 and 7), the rainy seasons only (columns 2, 5 and 8, and the dry seasons only (columns 3, 6 and 9). Season fixed effects are included. Standard errors in parentheses, clustered at the household level. Control variables included: Number of household members, Household head school attendance, total TLU owned (winsorized at 99 percent), share of camels in owned TLU, share of cattle in owned TLU, share of goats and sheep in owned TLU. The number of observations are slightly higher in the columns that only include pasture shocks of the previous season, as an additional observation of pasture quality can be included. Significance denoted by stars: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Pasture Condition on the Propensity to be Raided without Control Variables Concurrently, Lagged and Combined

	All Seasons	Rainy	Dry	All Seasons	Rainy	Dry	All Seasons	Rainy	Dry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Raided	Raided	Raided	Raided	Raided	Raided	Raided	Raided	Raided
Bad Pasture (v Normal Pasture)	0.00326**	0.00348	0.00359**				0.00341**	0.00208	0.00326*
	(0.00141)	(0.00234)	(0.00173)				(0.00142)	(0.00217)	(0.00179)
Good Pasture (v Normal Pasture)	-0.00146	-0.00230	-0.000507				-0.00131	-0.00275	-0.000622
	(0.00108)	(0.00174)	(0.00134)				(0.00109)	(0.00177)	(0.00130)
Bad Pasture Previous Season				-0.00102	-0.00226	-0.000857	-0.000556	-0.000480	-0.00115
				(0.00131)	(0.00257)	(0.00165)	(0.00133)	(0.00254)	(0.00164)
Good Pasture Previous Season				0.00306**	0.00813***	-0.00383***	0.00395***	0.00962***	-0.00335**
				(0.00144)	(0.00244)	(0.00134)	(0.00146)	(0.00244)	(0.00131)
N	27582	13291	14291	28477	14166	14311	27582	13291	14291
Mean	0.00554	0.00765	0.00362	0.00610	0.00715	0.00499	0.00549	0.00630	0.00474
Seasons	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bitemporal							✓	✓	✓

Notes: This table shows the effect of exceptionally good pasture quality (>80th percentile of the historical NDVI z-score per season per region) and exceptionally bad (<20th percentile) pasture quality per season and region on the propensity to be raided, compared to normal pasture quality (between the 20th and 80th percentile). This is estimated for the concurrent season only (columns 1-3), for the previous season only (columns 4-6) and for both the concurrent and previous season in the same estimation (7-9). It is estimated using a household fixed effects analysis for all season-types pooled (columns 1, 4 and 7), the rainy seasons only (columns 2, 5 and 8, and the dry seasons only (columns 3, 6 and 9). Season fixed effects are included. Standard errors in parentheses, bootstrapped with 1000 iterations. No control variables included. The number of observations are slightly higher in the columns that only include pasture shocks of the previous season, as an additional observation of pasture quality can be included. Significance denoted by stars: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Pasture Condition on the Propensity to be Raided without Control Variables and without Temporal Fixed Effects
Concurrently, Lagged and Combined

	All Seasons	Rainy	Dry	All Seasons	Rainy	Dry	All Seasons	Rainy	Dry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Raided	Raided	Raided	Raided	Raided	Raided	Raided	Raided	Raided
Bad Pasture (v Normal Pasture)	0.00326**	0.00348	0.00359**				0.00341**	0.00208	0.00326*
	(0.00141)	(0.00234)	(0.00173)				(0.00142)	(0.00217)	(0.00179)
Good Pasture (v Normal Pasture)	-0.00146	-0.00230	-0.000507				-0.00131	-0.00275	-0.000622
	(0.00108)	(0.00174)	(0.00134)				(0.00109)	(0.00177)	(0.00130)
Bad Pasture Previous Season				-0.00102	-0.00226	-0.000857	-0.000556	-0.000480	-0.00115
				(0.00131)	(0.00257)	(0.00165)	(0.00133)	(0.00254)	(0.00164)
Good Pasture Previous Season				0.00306**	0.00813***	-0.00383***	0.00395***	0.00962***	-0.00335**
				(0.00144)	(0.00244)	(0.00134)	(0.00146)	(0.00244)	(0.00131)
N	27582	13291	14291	28477	14166	14311	27582	13291	14291
Mean	0.00554	0.00765	0.00362	0.00610	0.00715	0.00499	0.00549	0.00630	0.00474
Seasons	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bitemporal							✓	✓	✓

Notes: This table shows the effect of exceptionally good pasture quality (>80th percentile of the historical NDVI z-score per season per region) and exceptionally bad (<20th percentile) pasture quality per season and region on the propensity to be raided, compared to normal pasture quality (between the 20th and 80th percentile). This is estimated for the concurrent season only (columns 1-3), for the previous season only (columns 4-6) and for both the concurrent and previous season in the same estimation (7-9). It is estimated using a household fixed effects analysis for all season-types pooled (columns 1, 4 and 7), the rainy seasons only (columns 2, 5 and 8, and the dry seasons only (columns 3, 6 and 9). No season fixed effects or control variables are included. Standard errors in parentheses, bootstrapped with 1000 iterations. The number of observations are slightly higher in the columns that only include pasture shocks of the previous season, as an additional observation of pasture quality can be included. Significance denoted by stars: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Pasture Condition on the Propensity to be Raided: Quantiles Concurrently, Lagged and Combined

	All Seasons	Rainy	Dry	All Seasons	Rainy	Dry	All Seasons	Rainy	Dry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Raided	Raided	Raided	Raided	Raided	Raided	Raided	Raided	Raided
Bad Pasture (v Normal Pasture)	0.00353**	0.00364	0.00390**				0.00370**	0.00337	0.00407**
	(0.00154)	(0.00250)	(0.00186)				(0.00154)	(0.00251)	(0.00179)
Good Pasture (v Normal Pasture)	-0.00121	-0.00150	-0.000757				-0.00146	-0.00201	-0.000838
	(0.00117)	(0.00190)	(0.00146)				(0.00118)	(0.00190)	(0.00141)
Bad Pasture Previous Season				-0.00285**	-0.00550***	-0.000514	-0.00310***	-0.00547***	-0.00107
				(0.00119)	(0.00197)	(0.00157)	(0.00119)	(0.00195)	(0.00157)
Good Pasture Previous Season				-0.00310**	-0.00611***	-0.000501	-0.00346***	-0.00626***	-0.00116
				(0.00125)	(0.00205)	(0.00184)	(0.00121)	(0.00205)	(0.00177)
N	24752	12015	12737	24710	12015	12695	24710	12015	12695
Mean	0.00565	0.00779	0.00369	0.00771	0.0102	0.00475	0.00819	0.0111	0.00497
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Seasons	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bitemporal							✓	✓	✓

Notes: This table shows the effect of exceptionally good pasture quality (>75th percentile of the historical NDVI z-score per season per region) and exceptionally bad (<25th percentile) pasture quality per season and region on the propensity to be raided, compared to normal pasture quality (between the 25th and 75th percentile). This is estimated for the concurrent season only (columns 1-3), for the previous season only (columns 4-6) and for both the concurrent and previous season in the same estimation (7-9). It is estimated using a household fixed effects analysis for all season-types pooled (columns 1, 4 and 7), the rainy seasons only (columns 2, 5 and 8, and the dry seasons only (columns 3, 6 and 9). Season fixed effects are included. Standard errors in parentheses, bootstrapped with 1000 iterations. Control variables included: Number of household members, Household head school attendance, total TLU owned (winsorized at 99 percent), share of camels in owned TLU, share of cattle in owned TLU, share of goats and sheep in owned TLU. The number of observations are slightly higher in the columns that only include pasture shocks of the previous season, as an additional observation of pasture quality can be included. Significance denoted by stars: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Pasture Condition on the Propensity to be Raided: 15 and 85 percent Concurrently, Lagged and Combined

	All Seasons	Rainy	Dry	All Seasons	Rainy	Dry	All Seasons	Rainy	Dry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Raided	Raided	Raided	Raided	Raided	Raided	Raided	Raided	Raided
Bad Pasture (v Normal Pasture)	0.00368**	0.00379	0.00412**				0.00375**	0.00342	0.00467**
	(0.00152)	(0.00239)	(0.00196)				(0.00151)	(0.00243)	(0.00188)
Good Pasture (v Normal Pasture)	-0.00166	-0.00169	-0.00141				-0.00155	-0.00143	-0.00156
	(0.00135)	(0.00218)	(0.00178)				(0.00142)	(0.00230)	(0.00183)
Bad Pasture Previous Season				0.000589	-0.00141	0.00218	0.00117	-0.00127	0.00328
				(0.00170)	(0.00311)	(0.00214)	(0.00172)	(0.00320)	(0.00207)
Good Pasture Previous Season				0.00165	0.00346	-0.000130	0.00118	0.00265	0.0000629
				(0.00154)	(0.00242)	(0.00189)	(0.00153)	(0.00233)	(0.00192)
N	24752	12015	12737	24358	11965	12393	24358	11965	12393
Mean	0.00538	0.00743	0.00359	0.00596	0.00776	0.00415	0.00497	0.00801	0.00160
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Seasons	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bitemporal							✓	✓	✓

Notes: This table shows the effect of exceptionally good pasture quality (>15th percentile of the historical NDVI z-score per season per region) and exceptionally bad (<85th percentile) pasture quality per season and region on the propensity to be raided, compared to normal pasture quality (between the 15th and 85th percentile). This is estimated for the concurrent season only (columns 1-3), for the previous season only (columns 4-6) and for both the concurrent and previous season in the same estimation (7-9). It is estimated using a household fixed effects analysis for all season-types pooled (columns 1, 4 and 7), the rainy seasons only (columns 2, 5 and 8, and the dry seasons only (columns 3, 6 and 9). Season fixed effects are included. Standard errors in parentheses, bootstrapped with 1000 iterations. Control variables included: Number of household members, Household head school attendance, total TLU owned (winsorized at 99 percent), share of camels in owned TLU, share of cattle in owned TLU, share of goats and sheep in owned TLU. The number of observations are slightly higher in the columns that only include pasture shocks of the previous season, as an additional observation of pasture quality can be included. Significance denoted by stars: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Pasture Condition on the Propensity to be Raided: Estimated at Sublocation/Kebele level Concurrently, Lagged and Combined

	All Seasons	Rainy	Dry	All Seasons	Rainy	Dry	All Seasons	Rainy	Dry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Raided	Raided	Raided	Raided	Raided	Raided	Raided	Raided	Raided
Bad Pasture (v Normal Pasture)	0.00260	0.00171	0.00340*				0.00297*	0.00219	0.00196
	(0.00167)	(0.00287)	(0.00204)				(0.00168)	(0.00309)	(0.00222)
Good Pasture (v Normal Pasture)	-0.00459***	-0.00706***	-0.00215				-0.00435***	-0.00632***	-0.00364
	(0.00123)	(0.00207)	(0.00156)				(0.00151)	(0.00211)	(0.00260)
Bad Pasture Previous Season				-0.000378	-0.00343	0.00417*	-0.00117	-0.00322	0.00277
				(0.00169)	(0.00240)	(0.00227)	(0.00163)	(0.00237)	(0.00249)
Good Pasture Previous Season				-0.00325**	-0.00546***	-0.000365	-0.000530	-0.00237	0.00207
				(0.00135)	(0.00208)	(0.00165)	(0.00162)	(0.00219)	(0.00267)
N	25590	12829	12761	25590	12829	12761	25590	12829	12761
Mean	0.00742	0.0101	0.00457	0.00706	0.0107	0.00365	0.00746	0.0119	0.00366
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Seasons	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bitemporal							✓	✓	✓

Notes: This table shows the effect of exceptionally good pasture quality (>80th percentile of the historical NDVI z-score per season per sublocatoin or kebele) and exceptionally bad (<20th percentile) pasture quality per season and region on the propensity to be raided, compared to normal pasture quality (between the 20th and 80th percentile). This is estimated for the concurrent season only (columns 1-3), for the previous season only (columns 4-6) and for both the concurrent and previous season in the same estimation (7-9). It is estimated using a household fixed effects analysis for all season-types pooled (columns 1, 4 and 7), the rainy seasons only (columns 2, 5 and 8, and the dry seasons only (columns 3, 6 and 9). Season fixed effects are included. Standard errors in parentheses, bootstrapped with 1000 iterations. Control variables included: Number of household members, Household head school attendance, total TLU owned (winsorized at 99 percent), share of camels in owned TLU, share of cattle in owned TLU, share of goats and sheep in owned TLU. The number of observations are slightly higher in the columns that only include pasture shocks of the previous season, as an additional observation of pasture quality can be included. Significance denoted by stars: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Insurance Coverage, Insurance Indemnity Payments, Pasture Quality Last Season and Livestock Losses due to Raiding

	Dry Loss due to Raids (1)	Rainy Loss due to Raids (2)	Dry Loss due to Raids (3)	Rainy Loss due to Raids (4)
Predicted Insurance ($\gamma 1$)	-0.005604	-0.022997**	0.009025	-0.048829**
	(0.011492)	(0.008950)	(0.010883)	(0.021914)
Pred. ins. x index triggered ($\gamma 2$)			-0.096093	0.074475**
			(0.062727)	(0.037952)
Index triggered			0.010648***	-0.004575
			(0.003847)	(0.003362)
Good Pasture Last (v Normal Pasture)	-0.002919**	0.006378**	-0.001937	-0.003691
	(0.001300)	(0.002870)	(0.001398)	(0.003903)
Bad Pasture Last (v Normal Pasture)	0.000874	-0.003797	-0.002015	-0.004172
	(0.002283)	(0.003084)	(0.001829)	(0.008937)
Good Pasture Last x pred. ins. ($\gamma 3$)	-0.014291	0.037033	-0.012835	0.104515**
	(0.020870)	(0.040451)	(0.023104)	(0.049479)
Bad Pasture Last x pred. ins. ($\gamma 4$)	-0.035478	0.027070	-0.001167	0.062630
	(0.028718)	(0.044333)	(0.022355)	(0.099808)
Good Pasture Last x pred. ins. x index triggered ($\gamma 5$)			0.085773	-0.207057
			(0.079505)	(0.138652)
Bad Pasture Last x pred. ins. x index triggered ($\gamma 6$)			-0.061023	-4.972744
			(0.127814)	(6.228333)
Coef: $\gamma 1 + \gamma 2$			-0.087067	0.025646
p-value $\gamma 1 + \gamma 2$			*0.156946*	*0.355740*
Coef: $\gamma 1 + \gamma 3$	-0.019895	0.014035	-0.003810	0.055686
p-value $\gamma 1 + \gamma 3$	*0.274368*	*0.732046*	*0.854812*	*0.210037*
Coef: $\gamma 1 + \gamma 4$	-0.041082	0.004072	0.007858	0.013801
p-value $\gamma 1 + \gamma 4$	*0.135041*	*0.926851*	*0.719356*	*0.719356*
Coef: $\gamma 1 + \gamma 2 + \gamma 3 + \gamma 5$			-0.014130	-0.076896
p-value $\gamma 1 + \gamma 2 + \gamma 3 + \gamma 5$			*0.729015*	*0.522234*
Coef: $\gamma 1 + \gamma 2 + \gamma 4 + \gamma 6$			-0.149258	-4.884469
p-value $\gamma 1 + \gamma 2 + \gamma 4 + \gamma 6$			*0.110997*	*0.433769*
Household f.e.'s	✓	✓	✓	✓
Season controls	✓	✓	✓	✓
Control Mean Losses due to Raid	0.004682	0.008895	0.004682	0.008743
Observations	14311	14166	14310	9265