The Protective Role of Index Insurance in the Experience of Violent Conflict: Evidence from Ethiopia*

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Abstract

Droughts are among the leading causes of livestock mortality and conflict among pastoralist populations in East Africa. To foster climate resiliency in these populations, Index Based Livestock Insurance (IBLI) products have become popular. These products, which allow herders to hedge climate risk, often utilize remote-sensed data to trigger indemnity payouts, thus ameliorating moral hazard issues associated with standard insurance products. We study how one such program, implemented in southern Ethiopia, impacted the experience of violent conflict among participating households. Using a causal mediation analysis, we show first that there is a strong link between rangeland conditions and violent conflict; a one-unit decrease in a standardized version of the normalized difference vegetation index (zNDVI) in the previous season is associated with a 0.3-3 percentage point increase in the likelihood of conflict exposure. Within the mediation framework, we leverage a randomized encouragement experiment and show that insurance uptake reduces the conflict risk created by poor rangeland conditions by between 17 and 50 percent. Our results suggest that social protection programs, particularly index insurance programs, may act as a protective factor in areas with complex risk profiles, where households are exposed to both climatic and conflict risks, which themselves may interact.

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1 Introduction

Pastoralists in East Africa operate in complex risk environments threatening their livelihoods and ability to graduate from poverty (McPeak and Little, 2017; Barrett and Swallow, 2006; Coughlan de Perez et al., 2019). Potentially the most salient of these risks are prolonged droughts, which are likely to trigger food insecurity and may interact with other risks, such as those posed by violent conflict (Huho and Mugalavai, 2010; Ayana et al., 2016). These risks have grown concurrently over the recent decades. As prolonged droughts have caused widescale herd loss in the 1980s, 1990s, and 2010s, pastoralists have also faced more frequent and destructive violent conflict (Catley et al., 2016). It is not difficult to imagine these interacting events stunting the economic development of the populations in question.

In acknowledgment that household-level shocks may create poverty traps and prevent economic development, policymakers and stakeholders have long sought risk-reduction strategies that are cost-effective and scalable. One group of resiliency-improving interventions that has garnered popularity recently is index-based insurance products. Here, we study one of these interventions that is focused on insuring livestock. Index-based Livestock Insurance (IBLI) has been developed to allow pastoralist populations to hedge the risk of livestock mortality created by adverse weather events. They have expanded throughout the Horn of Africa, in part because they have been shown to increase household resiliency to shocks and improve livelihoods (Jensen and Barrett, 2017; Chantarat et al., 2013).

In this paper, we ask if the protective effects of IBLI products extend beyond the risks created by adverse weather events and study if insured households are less likely to be exposed to violent conflict. In doing so, we also study the interaction between household risks, asking if adverse weather events increase the likelihood of exposure to violence.

We may expect IBLI products to impact conflict risk for two reasons. In the immediate term, the indemnity offered by participation in IBLI reduces the incentive to practice satellite grazing[1] in the face of drought Toth et al. (2019). This may reduce their exposure to livestock raids and/or theft in remote areas away from the safety of their community. The second reason is that across seasons, we may expect IBLI participation to act as a protective factor against decapitalization caused by livestock mortality. This, in turn, may allow households the latitude to engage in activities that minimize conflict risk.

Concurrently, we expect adverse weather events to increase conflict risk by harming livelihoods and inducing households to engage in coping strategies. McGuirk and Nunn (2020) have shown that droughts have the potential to cause conflict as pastoralists engage

[1]Satellite grazing refers to a practice where pastoralists allow their livestock to graze in distant locations, away from their usual grazing areas, to access additional forage and water resources, thus easing the burden on their home rangelands.

in satellite grazing, potentially off-cycle, creating conflict with sedentary farmers using the land for cultivation. It is also plausible that households engage in raiding or other violent coping mechanisms in response to high levels of livestock mortality.

To answer the questions posed above, we study the impacts of the IBLI pilot program conducted by the International Livestock Research Institute (ILRI) and its partners (Cornell University, the University of Sydney, Syracuse University, and UC-Davis) in Southern Ethiopia on the experience of violent conflict in both self-reported data and data collected by the Armed Conflict Location and Event Data Project (ACLED). We leverage a randomized encouragement experiment included in the rollout of the program within a causal mediation framework linking rangeland conditions to program uptake and the experience of violent conflict. First, we demonstrate a strong link between rangeland conditions, conflict experience and program uptake; households who have experienced drought are at greater risk of conflict and are more likely to purchase insurance in the subsequent season.

These relationships mean that a naive correlation between IBLI uptake and conflict would suggest IBLI uptake increases conflict. However, there are several challenges to estimating this causal relationship. First, as stated above, weather events may confound any estimation as they impact both conflict risk and insurance preferences. Second, previous conflict experience may also influence program uptake. For instance, Rockmore and Barrett (2022) demonstrate in their study in northern Uganda that aggregate exposure to violence, whether experienced by oneself or a family member, affects individual risk preferences, but the effects vary depending on the nature of the individual's history of exposure to different types of violence. Similarly, Voors et al. (2012) has shown that conflict exposure among households in Burundi reduced risk aversion during a set of preference-eliciting games. If this relationship holds in our setting, and conflict risk is correlated over time, this would introduce simultaneity into our estimation and bias our results. For these reasons, we instrument for IBLI uptake in our estimations using randomly distributed discount coupons that were distributed as part of the pilot program's encouragement design and have been shown to be predictive of program uptake (Tafere et al., 2019; Takahashi et al., 2019). Using this design, we demonstrate that IBLI is protective against conflict and reduces the conflict risk created by drought by 17 to 50 percent depending on the measure of conflict.

Our findings contribute to two growing bodies of literature. The first relates to the role of index insurance programs in risk management, resilience building, and poverty reduction. This literature has shown that households participating in index insurance programs exhibit greater resiliency to shocks and improved livelihoods, the benefits of which very likely outpace the insurance premiums associated with the products (Jensen et al., 2017; Janzen and Carter, 2019). The second body of literature links drought events to conflict risk. Within this literature, the works that relate most closely to ours, Gatti et al. (2021) and McGuirk and Nunn (2020), find that drought events are linked to conflict and that irrigation interventions can attenuate this relationship in both Indonesia and the Sahel. To these bodies of work, we contribute what we believe to be the first analysis examining index insurance programs' role in attenuating the link between drought and violent conflict.

In addition to the above discussion on knowledge contribution, we also make a methodological contribution to the literature on causal mediation analysis. Previous works, such as Dippel et al. (2020), have dealt with endogeneity in the mediation framework by using instrumental variables for both treatment and mediator assignment. This paper considers a treatment, drought exposure, that is plausibly exogenous to our outcome and mediator. This leaves us with potential endogeneity for only our mediating variable. Our 2SLS framework is implemented by instrumenting the mediator by exploiting a randomized control trial that created exogenous variation in our mediator (IBLI purchase).

The remainder of this paper is organized as follows. Section 2 introduces background information on the study areas and IBLI program. Section 3 discusses the conceptual framework, focusing on the potential mechanisms. Section 4 describes the data sources and measurement of key variables of interest and presents descriptive results. Section 5 presents the proposed causal mediation analysis. Section 6 presents the main results. Finally, section 7 concludes.

2 Study Design

The program studied here was implemented in the Borena zone of Southern Ethiopia. The Borana zone consists mainly of arid lowlands with small intermixed areas of semi-arid agroecological zones, which display higher productivity rangeland conditions. The population in the Borena zone has historically been migratory pastoralists, though there has been a shift to sedentarization and agro-pastoral livelihood in higher potential areas. Across the zone, rangelands are subject to a bimodal rainfall pattern consisting of four seasons: 1) the long rainy season (LR) between March and June, 2) the long dry season (LD) between July and September, 3) The short rainy season (SR) during October and November, and 4) the short dry season (SD) between December and February (Vrieling et al., 2013).

2.1 Pastoralists and Agro-Pastoralists in Ethiopia

The populations living in southern Ethiopia, and Borena specifically, utilize pastoralism and agro-pastoralism as their dominant livelihood strategies (Anderson et al., 2021). The livestock production systems in these areas are characterized by cyclical migrations in search of grazing land and water and are subject to various risks. These risks can be man-made, such as those from climate change and conflict, or natural, including disease and predation. These risks have the potential to negatively impact livelihoods at the household level and stunt the economic growth of the system more generally.

Among the most salient risks that pastoralists face are those created by extreme weather events. Within these communities, frequent catastrophic droughts result in significant herd losses (Lybbert et al., 2004). For instance, droughts in the 1980s, 1990s, and from 2011 to 2012 (the year in which IBLI was launched in Ethiopia) resulted in significant herd losses in affected areas (Catley et al., 2016). The risk of these severe droughts exposes pastoralists to the potential of large negative income and asset shocks. However, as we explore throughout this paper, these may trigger additional related shocks, such as an increased risk of violent conflict (Kiondo et al., 2019).

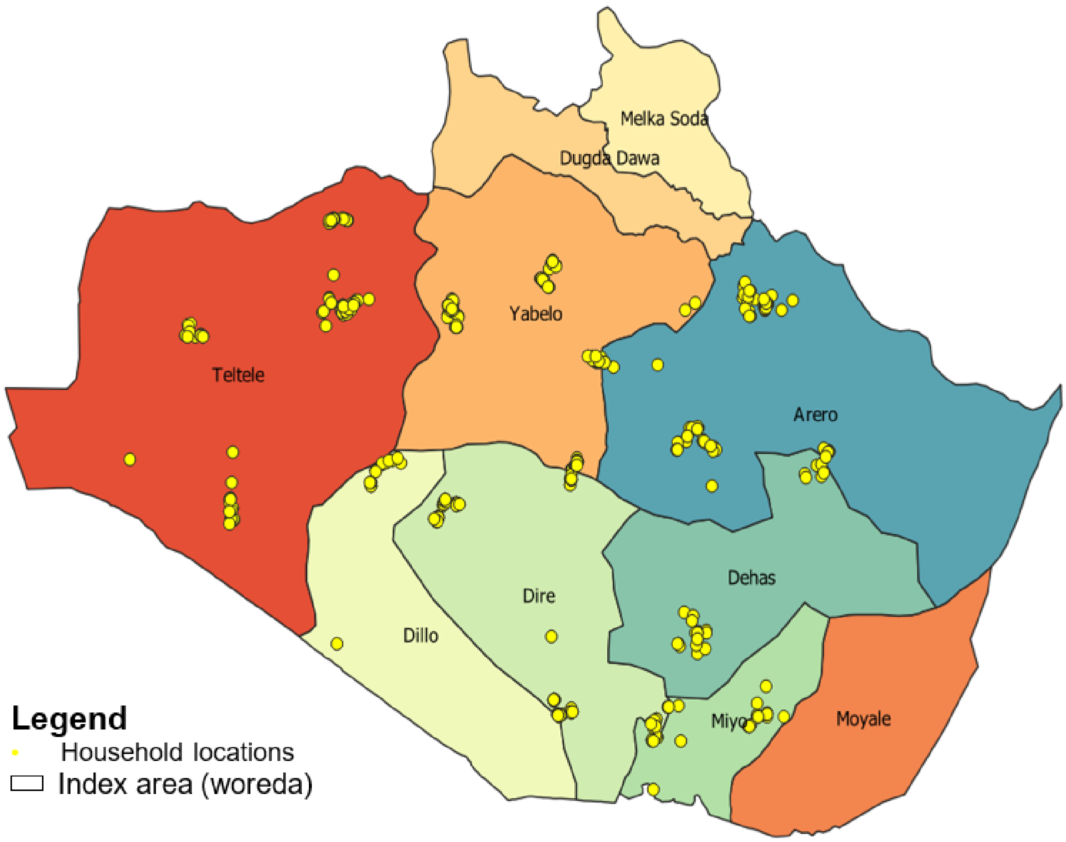
Index-based Livestock Insurance (IBLI) was designed in response to these shocks to allow members of pastoralist communities to manage climate-related risks and foster food and income security (Chantarat et al., 2013; Santos and Barrett, 2011). While there is a strong body of evidence to say that these programs have improved food security and resilience to shocks, there is little empirical evidence on how these interventions might impact downstream outcomes. This study aims to begin bridging this evidence gap by studying one such outcome, exposure to violent conflict.

2.2 Index-based Livestock Insurance

In order to test the effectiveness of the newly designed product, ILRI and its partners introduced IBLI as part of a pilot program in eight Woredas of the Borena zone in 2012. The pilot zone was grouped into index areas corresponding to commonly recognized administrative boundaries. Figure 1 displays the study areas. More information about the program's administration can be found in Jensen and Barrett (2017).

The IBLI scheme insured households through an area-aggregated seasonal forage scarcity index derived from satellites. The normalized difference vegetation index (NDVI) is a numerical representation of photosynthetic activity for a given time period (in our case for each 10-day) for a given plot of land. With these repeated measures over time, the standardized measure of rangeland conditions within a small area can be computed. The measure can be expressed cumulatively and measured as the number of standard deviations the density of vegetation in a given area is from the historical average, taking an arbitrary starting point

Figure 1: IBLI Pilot Index Areas



Notes: Figure depicts the Borena zone of southern Ethiopia with administrative boundaries. Yellow dots in each index area indicate the locations of randomly selected households.

as zero[2] (zNDVI). In Ethiopia, there were no appropriate data to be used to model livestock mortality as a function of cumulative zNDVI. So, instead, policies were developed using an index of NDVI anomalies directly, called 'forage scarcity contract' (Vrieling et al., 2013). Insured herders were designated to receive indemnity payouts when the measured index fell below the 15th percentile of the index history over 30 years. Since payouts were based on the realized zNDVI readings for a given LRLD or SRSD season, IBLI circumvented moral hazard issues related to individual loss claims. However, this indemnity scheme may have also been subject to an imperfect correlation between the payouts and experienced losses. This created the possibility of uninsured losses or the trigger of an indemnity without true losses (Jensen et al., 2016).

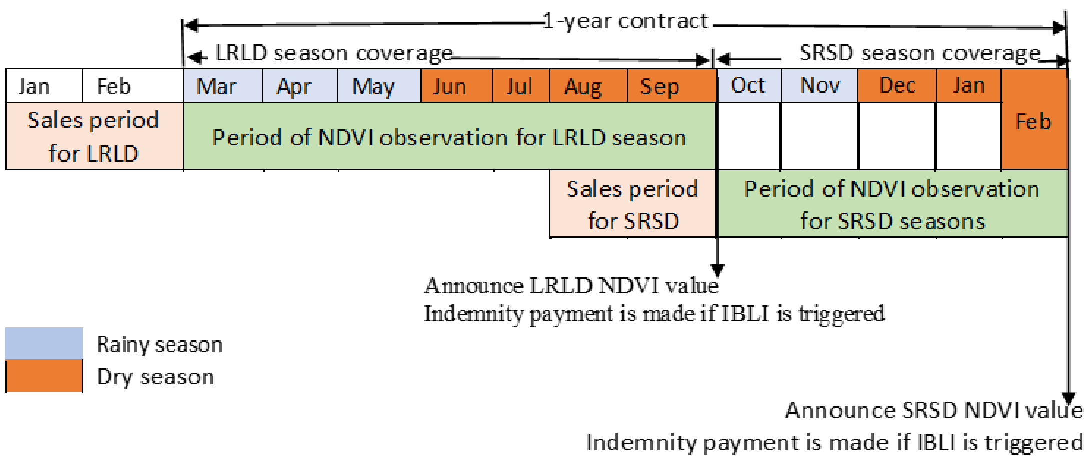
The Borena Zone of Ethiopia was divided into eight insurance units during the study period as illustrated in Figure 1. Premium rates and payout rates were determined at the index unit, and rates were constant within the unit. Most households in the study area owned

[2]For our study, we begin the measurement of the zNDVI in October of 2012.

herds composed of a combination of cattle, camels, goats, and sheep. Households choose the amount of insured coverage for each animal species as expressed in Tropical Livestock Units (TLU).[3]

Households could purchase IBLI contracts during two sales windows each year: before the start of the short rainy (SR) season and the long rainy (LR) season.[4] Contracts provided coverage for 12 months starting immediately after each sales period, creating an overlap of the insurance coverage periods of two IBLI contracts. Figure 2 describes the periods for insurance sales, coverage, and indemnity payouts. We see that IBLI purchases were available for purchase at the end of each dry season, and indemnity payouts for a given contract would be announced directly following the subsequent sales period.

Figure 2: IBLI Coverage Calendar



Notes: IBLI calendar is 1-year contract coverage and is divided into two insurance seasons: LRLD and SRSD season coverage. The calendar year has 2 months sales windows, just prior to the start of long rainy and short rainy seasons, i.e., Jan-Feb and Aug-September sales periods.

2.3 Encouragement Design

In our analysis, we leverage households' random assignment during an encouragement experiment to predict their eventual uptake of the IBLI product. As such, it is worth taking the time to discuss here. During the pilot in question, two different encouragement strategies were randomly offered to households to create exogenous variation in program uptake. In the first, nontransferable discount coupons were distributed to survey participant households

[3]1 TLU is based on 250kg live weight and 1 TLU=0.7 camels=1 cattle=10 sheep=10 goats

[4]As shown in Figure 2, the short rainy season consists of October and November, while the long rainy season spans March, April, and May

before each sales season began. Distribution took place at the insurance area level, the same level as the randomization. Prior to each round, approximately 80 percent of the respondents received a discount coupon, the value of which was randomly assigned and ranged from a discount of 10 percent to a discount of 80 percent at 10 percent intervals. For each coupon, households were able to purchase up to 15 Tropical Livestock Units (TLU) worth of insurance at the discounted price. Households with discount coupons were allowed to purchase insurance beyond the allotted 15 TLUs. However, these additional units were eligible for purchase at the standard index area premium.

3 Conceptual Framework

In this analysis, we have two central hypotheses. First, there is a causal link between rangeland conditions and conflict risk. Second, social protection programs, in this case, IBLI, have the potential to attenuate this link. There is much discussion elsewhere (Burke et al., 2015; Butler and Gates, 2012; Harari and Ferrara, 2018) about why we expect our first hypothesis to hold. In this section, we focus on our second hypothesis and the theoretical framework underlying our expectations.

The causal framework underlying our priors about the drought-conflict-insurance nexus is analytically complex. However, we expect IBLI to mediate conflict risk through five main mechanisms: 1) consumption smoothing and asset protection, 2) livelihood diversification, 3) adoption of drought-tolerant technologies, 4) altered mobility patterns, and 5) informal risk sharing.

Our first proposed mechanism operates directly through the indemnity payout associated with the IBLI program. To cope with drought shocks, poor households with inadequate access to credit markets and other resources may use destructive risk mitigation strategies, such as distressed livestock sales, to smooth household consumption, or they may cut their consumption to protect their assets (Barrett et al., 2019). IBLI is explicitly designed to protect against these harmful coping strategies by providing liquidity injections during periods of high livestock mortality (Chantarat et al., 2013; Janzen and Carter, 2019; Janzen et al., 2021) and protect households from falling into poverty traps. If we believe that poverty and decapitalization have the potential to fuel conflict, then it follows naturally that the protection the IBLI indemnity offers in the face of drought should decrease conflict risk.

The second related mechanism centers around the diversification of livelihoods. Previous research has shown that index insurance products incentivize households to diversify their livelihood activities to non-farm employment (Mobarak and Rosenzweig, 2012; Cole et al., 2017). We may expect this diversification to impact conflict in two ways. First, we may expect the transition to sedentary activities to change migration patterns in the face of drought. We will discuss this possibility more in-depth later in this section. Second, the diversification of livelihood activities may itself act as a protective factor against harmful coping strategies in the face of drought if the income gained from those activities is not directly affected by the incidence of drought. If this were to be the case, we would expect IBLI-induced livelihood diversification to impact conflict in a similar manner to the indemnity payouts themselves.

The third mechanism, which is in itself a subset of the second, relates to the type of activities households diversify toward. There is some evidence suggesting that index insurance coverage incentivizes households to adopt drought-resilient agricultural technologies (Cole et al., 2017). These drought-resilient technologies likely accentuate the protective effects described above.

Fourth, much of the literature relating drought incidence to conflict risk discusses the link working through herd mobility. Put simply, as pastoralists face drought, they push into areas that are further from the home community and are closer to the frontier of the grazing lands associated with their home community. In the West African context, McGuirk and Nunn (2020) has shown that this migration may cause friction with sedentary populations. In the East African context, we hypothesize this migration exposes pastoralists to risks of raiding and theft at higher rates than they would otherwise face in the safety of their communities. We hypothesize that uninsured households are more likely than insured households to adopt migration as a coping mechanism, potentially as a result of the livelihood diversification discussed earlier. Thus, we may expect households to be less susceptible to violence as a result of IBLI participation.

While all of the mechanisms that we have discussed above imply that IBLI should reduce the conflict risk faced by households, there exists one mechanism that may imply an alternative hypothesis. Previous research has shown that formal insurance may crowd out social capital and informal insurance networks (Cecchi et al., 2016). If this relationship holds in our setting, it may be the case that IBLI crowds out informal institutions used for dispute resolution and risk-sharing, which would naturally have negative consequences for peace, stability, and social harmony (Hample, 2021). There is some evidence that suggests this relationship does not hold in the case of IBLI (Takahashi et al., 2019), however, this possibility still provides the alternative hypothesis that IBLI may increase conflict risk.

In summary, the (IBLI) intervention we examine here is predicated on the notion that even small insurance interventions aimed at protecting assets or reducing income shocks can have considerable short-term and/or long-term impacts by providing insurance against drought-related herd mortality and poverty traps. We expect that this, in turn, may have a significant impact on the experience of violent conflict. Data limitations, to be discussed in the next section, prevent us from explicitly testing the mechanisms discussed above. However, this framework provides useful insight into why we may expect a link between conflict and insurance uptake.

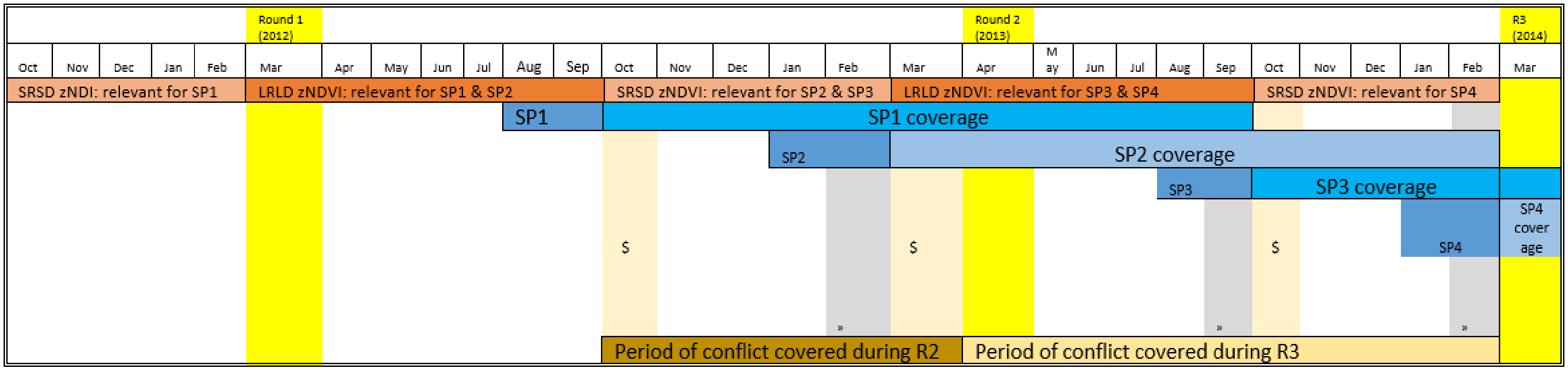
4 Data

This study uses data from several sources: a household panel survey associated with the IBLI pilot collected from pastoralists and agro-pastoralist communities in southern Ethiopia annually over four years (2012-2015), administrative data from insurance companies on IBLI purchases, remotely sensed datasets of rangeland conditions in the IBLI index areas and data on conflict events from the Armed Conflict Location and Event Data Project (ACLED).

Alongside the initial launch of the IBLI product, multiple rounds of surveys were conducted to evaluate the program's effectiveness on a range of outcomes. As such, a panel of 513 households was surveyed annually between 2012 and 2015 (four rounds). Attrition across rounds of the survey was less than 4 percent, and the survey collected information on a range of household characteristics, including demographic characteristics, herd composition, economic roles and herd mobility, risk perception (insecurity, violence, fights, raiding-both incidence and intensity of violent conflicts experienced), social capital, and livestock production. In Figure 3, we show a timeline relating the survey periods for each of the waves to the IBLI sales cycle discussed in Section 2.2. For our analysis, we utilize this dataset and match household survey records to an administrative record of household IBLI purchases.

To measure rangeland conditions and the incidence of drought, we use a cumulative and standardized version of the Normalized Difference Vegetation Index (zNDVI). The zNDVI is a measure of the seasonal forage scarcity indices from the Moderate Resolution Imaging Spectroradiometer (MODIS) at lower level spatial resolution (about 250 m resolution) with a temporal frequency of overlapping 10 days interval (dekad) as an indicator of seasonal forage availability (Vrieling et al., 2016a).The NDVI values are averaged for all pixels in the index areas shown in 1 for all dekads associated with each of the four rainy season dry season periods illustrated in 2, and then seasonally averaged to obtain a single value for each unit. An anomaly index is then generated by subtracting the index unit mean of this index across all seasons and dividing that difference by the index unit standard deviation of that index. As such, the zNDVI anomaly is computed for each index unit (at woreda) and for each agricultural season. Finally, to measure conflict, we use both the self-reported conflict data from the household panel described above, as well as conflict data from the ACLED project. Below, we describe in greater detail how each of the main variables used in our mediation analysis is measured.

Figure 3: Temporal Structure of NDVI recordings, Household Surveys, and IBLI sales



Notes:LRLD refers to long rain/long dry season from March through September. SRSD refers to the short rain/short dry season, from October through February. SP1 refers to IBLI sales period 1 in August-September; SP2 rers to sales period 2 in January-February, and so on. ¿¿ denotes NDVI index announcement and $ Potential payout. At least two zNDVI observations (i.e. LRLD zNDVI and SRSD zNDVI) before SP1 are likely to influence purchases, hence relevant Treatments for R2. For instance, for SP1 in August-September (SP1), relevant zNDVIs observations are SRSD 2011 and LRLD 2012. A household can have up to three active purchases or policies during a survey reference period (IBLI calendar year). Round 4 in 2015 is not presented due to formatting considerations in creating the figure, but it follows the pattern established by the earlier rounds that are illustrated in the figure.

4.1 Key Variables

Within our meditation framework, we use three key variables: weather shocks, IBLI participation, and conflict exposure. In the sections below, we briefly describe the construction of each of these variables.

4.1.1 Weather Shocks

We measure rangeland conditions and their reactions to weather events throughout our analysis using the zNDVI measure. Using this measure allows us to be consistent with IBLI's implementation policy, as contracts and indemnities are based on the measure. We discuss the technical measurement of the index in Appendix A. In terms of interpretation, negative zNDVI implies that the vegetation in a given pixel is worse than the average for that area over the period of satellite data collection. Values around 0 point imply normal rangeland conditions, and values greater than 0 imply better-than-average conditions.

As a robustness check for our analysis, we also report robustness checks using alternative measures of rangeland conditions such as the Enhanced Vegetation Index (EVI) and Modified Soil Adjusted Vegetation Index (MSAVI). Details on these alternatives can be found in A.

4.1.2 IBLI Participation

We measure a household to have participated in IBLI if administrative data shows them having purchased insurance for their livestock. We consider IBLI participation on both the intensive and extensive margin by including it in our mediation analysis as a dummy variable, in addition to the number of TLUs worth of insurance purchased.

4.1.3 Conflict Exposure

We capture households' conflict exposure in three ways: self-reported experience of households to conflict, proximity to conflict points, and statistical risk of conflict exposure. Our self-reported conflict measure is drawn from the IBLI pilot household surveys and is measured as a dummy variable that takes the value 1 if a household reports livestock loss due to raiding, rustling, or conflict in the previous year.

For a more objective measure of conflict exposure, we use the ACLED dataset to create two variables for conflict exposure within a 50-km radius during a given season. The first of these is a dummy variable that takes the value one if there is a reported conflict event within the radius. The second is a continuous variable that records the number of conflict fatalities within the radius.

Finally, we follow Rockmore (2016) and calculate households' statistical risk of conflict exposure as:

$$ln\frac{Pr(C_{it}=1)}{1-Pr(C_{it}=1)} = \delta + \sum_{s=LR/SR}^{LD/SD} \alpha_{ist} dist_{ist} + \epsilon_{it} \tag{1}$$

where C_{it}, is a binary variable equal to one if household i had ever experienced conflict at base or satellite camp in year t. The variable, $dist_{ist}$, represents the distance of a household i from the closest conflict points as reported in ACLED data in season s in year t. ϵ_{it} is the error term. The predicted value from Equation 1 is, thus, the estimated probability that a given household experiences conflict within a season.

4.2 Descriptive Statistics

Table 1 presents summary statistics for our main variables of interest. We see that about 9 percent of households are exposed to conflict within 50 km of their residence. About 33 percent of households in our sample self-report that the pressing concern or risk to their household is insecurity or conflict. In terms of the statistical risk of conflict, we find that the risk at the household level is similar to the actual conflict experience reported by households. Approximately 34 percent of the households purchased IBLI at least once at the time of survey. There are no households that purchased in each sales period. In each sales period, about 77 percent of households in the sample had received discount coupons. The first indemnity payments were made in the last rounds. During the study period, the shortage of forage was more severe during LRLD season than SRSD season based on patterns in cumulative zNDVI values.

5 Empirical Strategy

In our analysis, we implement a novel version of the causal mediation-IV framework developed by Dippel et al. (2020). A causal mediation analysis is a structural equation model that aims to identify the causal mediation effect:

$$\delta(t) = Y_i\left(t, M_i(1)\right) - Y_i\left(t, M_i(0)\right) \tag{2}$$

where t is represents the state of a treatment variable and $M_i(t)$ represents a temporally downstream mediating variable under treatment state t. In plain English, the causal mediation effect represents the change in the outcome variable, Y_i, that results from changes in the mediator, $M_i(t)$, driven by the treatment state. In our setting, this translates to the

Table 1: Descriptive Statistics for Selected Variables

Key Variables	Observations	Mean	Standard deviation	Min	Max
Conflict outcomes					
Self-reported major concern or risk is insecurity/violence/fights	1533	0.33	0.469	0.00	1.00
Household experienced Raiding/Conflict	1533	0.26	0.439	0.00	1.00
Conflict exposure within 50km based on ACLED dataset	1532	0.09	0.285	0.00	1.00
Number of fatalities within 50km based on ACLED dataset	1532	0.13	0.630	0.00	5.00
Statistical Risk of Conflict Exposure	1533	0.25	0.037	0.23	0.36
Rangeland Conditions					
LRLD zNDVI value prior to IBLI purchase	1532	-3.26	11.468	-27.33	27.85
SRSD zNDVI value prior to IBLI purchase	1532	5.14	4.462	-1.43	13.86
Animals lost due to drought or starvation					
IBLI coverage					
A household purchased IBLI	1533	0.34	0.473	0.00	1.00
A household purchased IBLI in August-September sales period	1532	0.25	0.434	0.00	1.00
A household purchased IBLI in January-February sales period	1532	0.14	0.351	0.00	1.00
Total number of TLUs insured, conditional on purchase	517	1.91	4.671	0.00	30.00
Coupons					
A household received discount coupons	1532	0.77	0.418	0.00	1.00
A household received audiotape	1532	0.05	0.228	0.00	1.00
A household received comic book	1532	0.03	0.165	0.00	1.00

Notes: See Table A for a description of each variable. Summary statistics cover only round 2 (the year in which IBLI first became available) through 4 of the IBLI pilot surveys.

change in conflict risk created by drought-induced IBLI purchases.

The fundamental problem of causal inference implies that we are unable to observe both $Y_i(t, M(1))$ and $Y_i(t, M(0))$, implying that the causal meditation effect is empirically unidentified. However, Imai et al. (2010) shows that the *average causal mediation effect* (ACME), $\bar{\delta}(t) = E[Y_i(t, M_i(1)) - Y_i(t, M_i(0))]$ can be parametrically identified within a Baron and Kenny (1986) Linear Structural Equation Model (LSEM). Within our analysis, this structural equation model takes the form:

$$Y_{iat} = \beta_1 T^{LRLD}_{a,t-1} + \beta_2 T^{SRSD}_{a,t-1} + X_{iat} + \Phi'_i + v_i + \epsilon_{iat} \tag{3}$$

$$M_{iat} = \alpha_1 T^{LRLD}_{a,t-1} + \alpha_2 T^{SRSD}_{a,t-1} + X'_{iat} + \Phi'_i + v'_i + \varepsilon_{iat} \tag{4}$$

$$Y_{iat} = \delta_1 T^{LRLD}_{a,t-1} + \delta_2 T^{SRSD}_{a,t-1} + \delta_3 M_{iat} + X''_{iat} + \Phi''_i + v''_i + \mu_{iat} \tag{5}$$

Where Y_{iat} is the outcome variable of interest (i.e., conflict variables) for household i in index area a in year t. Here t is the 12-month period before the interview, which is the period of insurance coverage or IBLI calendar year. M_{iat} is the mediating variable and represents the insurance uptakes by the household over the three recent sales seasons at period t (i.e. total number of active policies at period t). As indicated in Figure 1, up to three relevant IBLI sales periods could potentially affect a household's conflict behavior. $T_{a,t-1}$ is our treatment variable, i.e. the LRLD pasture availability index (zNDVI) for index area, a, in year $t-1$ or the SRSD pasture availability index (zNDVI) for index area, a, in year $t-1$. X_{iat} represents a set of covariates described earlier. It also accounts for other time-trending variables, such as gradual demographic changes that could be correlated with both weather shock and conflict. Φ_i represents location-specific fixed effects because of any number of cultural, historical, political, economic, geographic, or institutional differences between the locations/index areas. v_t is year/round fixed effects, and ϵ_{iat}, ε_{iat}, and μ_{iat} are the error terms clustered at the household level.

Within the above model, the ACME is identified by $\alpha_1\delta_3$ under two assumptions defined by Imai et al. (2010). First, the common support assumption states that the probability of treatment, conditional on a mediating variable and covariates, is non-zero for all treated units. Here, we use a continuous treatment variable (rangeland condition), which is defined as the state of an area relative to its long-run trend. Thus, we expect that each unit has the possibility of both positive and negative years, meeting this assumption.

The second identifying assumption, referred to as the sequential ignorability assumption, is formally defined as:

$$\{Y_i(t', m), M_i(t)\} \perp\!\!\!\perp T_i | \mathbf{X}_i = \mathbf{x} \tag{6}$$

$$Y_i(t', m) \perp\!\!\!\perp M_i(t) | T_i = t, \mathbf{X}_i = \mathbf{x} \tag{7}$$

for all t, t'.

In our context, condition 6 implies that there exists no characteristic, other than those contained in the covariate set $\mathbf{X}_i$, that influences both rangeland conditions and either IBLI uptake or conflict. As rangeland conditions are largely a proxy for weather conditions, which are plausibly exogenously determined, we have strong reason to believe this assumption holds.

In contrast, for condition 7 to hold, we must be able to assume that IBLI purchases are not simultaneously determined with conflict exposure. This is much more difficult to justify, and we do not expect it to hold in practice. As households self-select into program participation, it is natural to expect that conflict may, at some level, influence those decisions. To expand on this point more concretely, it is easy to imagine that those who choose to purchase IBLI are also likely those who benefit the most from livestock insurance. For households with a high risk of conflict, their basis risk is more diversified than other households and includes types of risk that are not covered by the IBLI scheme. Therefore, IBLI acts as a less effective hedge for these households; thus, conflict risk may directly impact purchasing decisions. Indeed, previous studies, such as Jensen et al. (2018), that IBLI purchases are driven by basis risk, including the risk of conflict.

As such, we expect that our setting violated the traditional Imai et al. (2010) sequential ignorability assumption. To cope with the empirical challenge this creates, we follow Dippel et al. (2020) and combine our mediation analysis with an instrumental variable estimation. We do so by exploiting a randomized encouragement experiment that was initially used to test the effectiveness of IBLI. In doing so, we instrument IBLI takeup with randomly distributed coupons that provided premium discounts for those that purchase IBLI, denoted as Z_iat in our estimations below. Previous studies have also used these variables to instrument for insurance coverage, though not in the context of mediation analysis (Tafere et al., 2019; Takahashi et al., 2019).

In order for the validity of our instrument to hold, two assumptions must first be met. First, we must assume that distributed coupons significantly impact a household's probability of participating in IBLI. In Table 3, we display the results from our first-stage estimation and show that the F-statistics associated with our instruments imply relevance when using a binary indicator but are weaker in relation to the number of TLUs insured. This may suggest that coupons increased the probability of purchases at the household level but not the amount insured.

Second, we must assume that conflict risk is not impacted by coupon distribution in a way other than through purchasing IBLI. On its face, we expect this assumption to hold as the coupons are randomly distributed and do not impact households in a way other than the price of the insurance product.

Satisfied with the validity of our instrument, we implement the following structural model:

$$M_{iat} = \alpha_1 Z_{iat} + \alpha_2 T^{LRLD}_{a,t-1} + \alpha_3 T^{SRSD}_{a,t-1} + X_{iat} + \Phi_i + v_i + \epsilon_{iat} \tag{8}$$

$$Y_{iat} = \delta_1 T^{LRLD}_{a,t-1} + \delta_2 T^{SRSD}_{a,t-1} + \delta_3 \hat{M}_{iat} + X'_{iat} + \Phi'_i + v'_i + \varepsilon_{iat} \tag{9}$$

where $\hat{M}_{iat}$ represents the predicted values of M_{iat}, and Z_{it} represents the value of a randomly assigned discount coupon. Within this framework, δ_3 represents the direct impact of IBLI purchases on conflict risk in a standard 2SLS framework. Meanwhile, $\delta_3\alpha_2$ and $\delta_3\alpha_3$ represent the ACME of IBLI for rangeland conditions in the LRLD and SRSD seasons, respectively.

6 Results

This section empirically describes the causal chain between rangeland conditions and conflict risk. We focus on the potential protective role of IBLI participation in this causal link.

6.1 Rangeland Conditions and Conflict Exposure

Before exploring IBLI and its associated impacts, we first explore the direct link between rangeland conditions and conflict risk. In Table 2, we display estimates of the association between zNDVI scores and conflict exposure in the subsequent year. We display results for all five of our conflict measures. Consistently across measures, we find that greater LRLD season forage availability before the IBLI sales period tends to decrease households' conflict exposure. Meanwhile, the associations with forage conditions in the SRSD season are more mixed. Here, we observe a negative association with self-reported measures of conflict but positive associations with the ACLED conflict measures. In terms of magnitude, we observe that a one-standard-deviation (SD) improvement (toward greener) in the LRLD season zNDVI values is associated with a 0.3 to 0.5 percent decrease in households' experience of conflict. Similarly, we estimate that a one SD increase in LRLD zNDVI values decreases the likelihood of conflict occurrence and the number of fatalities within 50 km of conflict points by about 1 percent and 0.03 deaths, respectively. The Wald test for joint significance of the coefficients for LRLD and SRSD zNDVI strongly rejects the null of jointly insignificant treatment across estimations.

Our results are in line with findings from previous studies, and the magnitude of our estimates is within the range found in other comparable studies in the region. For instance, Hsiang et al. (2013) find that a temperature increase by one (within-cell) SD translates into an increased conflict likelihood of 71 percent in Kenya; similarly, Maystadt et al. (2015) find an effect of 31 percent for North and South Sudan. A meta-analysis of 55 studies by Burke et al. (2015) also suggests a positive relationship between warmer temperature and conflict: 1 SD increase in temperature increases interpersonal conflict by 2.4 percent. Our result is also consistent with other comparable studies in the Sahel region. For instance, McGuirk and Nunn (2020, p.1) find that "droughts in the territory of transhumant pastoralists lead to conflict in neighboring areas", sedentary agricultural areas where conflict events are concentrated. In addition, the positive relationship between SRSD season zNDVI and conflict exposure is in line with the previous findings from East Africa, where high seasonal rainfall caused greater growth of vegetation that was used as cover for cattle raids in East Africa, giving aggressors a strategic advantage for cattle theft. This is also in line with McGuirk and Nunn (2020), who find that more conflict occurs during the wet and not the dry seasons,

Table 2: Rangeland Conditions and Conflict Exposure

	(1)	(2)	(3)	(4)
	Self-reported conflict/violence experience	ACLED within 50 KM conflict exposure	ACLED Fatalities within 50 KM	Statistical Risk of Conflict
Season:				
LRLD zNDVI during Previous Year	-0.003***	-0.005***	-0.026***	-0.001***
	(0.001)	(0.001)	(0.004)	(0.000)
SRSD zNDVI during Previous Year	-0.017***	0.027***	0.019***	0.003***
	(0.004)	(0.004)	(0.006)	0.000
Joint F-stat: zNDVI	11.29	46.5	38.44	80.44
Prob>F: zNDVI	0.000	0.000	0.000	0.000
Mean of conflict (Dep. var of never purchased IBLI)	0.33	0.08	0.12	0.25
Observations	1466	1466	1466	1466
Number of households	515	515	515	515
Model F-stat	7.04	18.27	14.25	70.33
Adj.R2	0.22	0.50	0.34	0.54
Round FE	Yes	Yes	Yes	Yes
Index area FE	Yes	Yes	Yes	Yes

Note: Columns 1 and 2 report the linear probability model (LPM) estimates of conflict exposure. All the models include the following control variables, in addition to round and index-area fixed effects: female-headed dummy, sex and age of household head, age of head squared, household size (adult equivalence), educational level of household head, a dummy indicating the head of household is a married, IBLI knowledge, donkey owned, poultry owned, a dummy indicating membership in self-help group, irrigated land (ha), non-irrigated land (ha), herd size(TLU), herd loss(TLU), wealth index, a dummy indicating if hh member has migrated in the last 12 months, net transfer(log), a dummy indicating household tribe, and income(log). Robust standard errors clustered at the household level are in parentheses.
Statistical significance* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

although the West African context differs from that of the East African context in the nature of conflict.

We must note that the measured effects of rangeland conditions on conflict exposure that we observe are reasonably small. We surmise that two main factors can explain what we believe are attenuated effect sizes. First, in this setting, pastoralists are more likely to face low-intensity conflict as a result of property disputes than large-scale armed conflict. In these cases, ACLED is likely to underreport incidences due to its reliance on journalism for data collection (Raleigh and Kniveton, 2012). This means our outcome variables associated with the ACLED data are likely to be an underestimation of the true conflict prevalence. Second, while we cluster our standard errors throughout our analysis at the index level to match the level at which discount coupons are randomly assigned, the spacial construction of our outcome variable using ACLED data would naturally imply that there is spatial correlation between households in terms of conflict exposure. Further, it is unclear what level of clustering would ameliorate this issue. Even for our self-reported measures, there are likely to be significant within-group correlations that we are unable to account for.

6.2 Rangeland Conditions and IBLI Uptake

Regarding households' decisions to participate in the IBLI program, two associations are crucial to our causal mediation analysis. First, in order for IBLI to mediate the impacts of rangeland conditions on conflict, rangeland conditions themselves must determine IBLI purchases. Second, due to our instrumental variable framework, we must also be sure that the randomly distributed coupons that we use as our instrument have a strong impact on IBLI uptake.

In Table 3, we present results from estimations of rangeland conditions (Panel A) and discount coupons (Panel B) on IBLI uptake. In line with our priors, we observe that there is a strong association between rangeland conditions and IBLI purchases. Particularly for the LRLD season, we see a one standard deviation decrease in zNVDI increases the probability that a household purchases IBLI by 0.6 percentage points. However, we do not observe a strong effect on the amount of insurance purchased. Notably, we do not observe strong relationships between IBLI uptake and the conditions in the SRSD season. For this reason, when we conduct our mediation analysis in section 6.3, we focus our analysis using the zNDVI value for the LRLD season as our treatment of interest.

In the second panel of Table 3, we test the impacts of the randomly distributed discount coupons on IBLI uptake. We show that across sales periods, receiving discount coupons have a strong effect, increasing the probability of IBLI uptake by between 10.5 and 19.5 percentage points. On the intensive margin, we see that coupons increase the number of TLUs insured by 0.373. Regarding the strength of coupons as an instrument for IBLI uptake, we see that the instrument-specific F-statistics for the extensive margin imply strong relevance. However, on the intensive margin, we see much less relevance for our instrument. Therefore, our preferred mediator in our main mediation analysis in the next section is IBLI uptake at the extensive margin.

6.3 Mediation Analysis

Finally, we present the results of our mediation analysis in Table 4. In Panel A, we display the predicted coefficients for equation 9 on our defined conflict outcomes. In this panel, the coefficient on predicted IBLI uptake represents the 2SLS estimate of IBLI's direct impact on conflict outcomes. We observe that IBLI uptake has a strong negative significant effect on household conflict exposure irrespective of the conflict measures used. Our point estimates in columns 1 and 2 show that buying IBLI policy decreases households' likelihood of experiencing conflict (self-reported) by about 10 percentage points and intergroup conflict exposure within 50 km (ACLED data) by 18 percentage points. Both estimates are statistically sig-

Table 3: Impact of Rangeland Conditions and Discount Coupons on IBLI Uptake

	(1)	(2)	(3)	(4)
	LPM estimates of IBLI uptake: for either LRLD or SRSD season coverage	LPM estimates of IBLI uptake: August-September sales period	LPM estimates of IBLI uptake: January-February sales period	OLS estimates of volume of TLU insured
Panel A: Season before purchase				
LRLD zNDVI value before IBLI sales period	-0.006***	-0.003*	-0.005***	-0.017
	(0.002)	(0.002)	(0.002)	(0.016)
SRSD zCZNDVI value before IBLI sales period	0.008	0.012*	-0.006	-0.015
	(0.006)	(0.006)	(0.004)	(0.044)
Joint F-stat: zNDVI	8.37	4.8	4.67	0.78
Prob>F: zNDVI	0.000	0.008	0.009	0.459
Panel B: Discount coupon	0.195***	0.157***	0.105***	0.373**
	(0.015)	(0.014)	(0.013)	(0.153)
Observations	1,466	1,466	1,466	1,466
Model F-stat	22.72	13.57	7.37	3.29
F-stat instruments	155.39	118.78	65.43	5.92
R-squared	0.208	0.148	0.118	0.094
Round FE	Yes	Yes	Yes	Yes
Index-area FE	Yes	Yes	Yes	Yes

Note: The table presents the first stage estimates of IBLI uptake and TLU insured as a function of lagged LRLD and SRSD zNDVI values (T), randomized treatment assignment and other controls. Columns (1) to (2) show LPM estimates of IBLI uptake for LRLD/SRSD season coverage, only SRSD season coverage and only LRLD season coverage, respectively. As such the dependent variable IBLI uptake is a dummy variable that takes a value of 1 if a household buys IBLI during IBLI calendar year, i.e., survey reference period, and 0 otherwise. IBLI calendar year is divided into two insurance seasons: LRLD season coverage and SRSD season coverage and there are two sales periods in each survey round. A household can have up to three active purchases or policies during a survey reference period (i.e., IBLI calendar year). The dependent variable TLU insured is a continuous variable. TLUs stands for Tropical livestock units. Discount coupon is a dummy variable that takes a a value of 1 if a household received discount coupons at time of survey. All specifications include the following control variables, in addition to round and index-area fixed effects: female headed dummy, sex and age of household head, age of head squared, household size (adult equivalence), educational level of household head, a dummy indicating the head of household is a married, IBLI knowledge, a dummy indicating membership in self-help group, irrigated land (ha), non-irrigated land (ha), herd size(TLU), herd loss(TLU), wealth index, net transfer(log), a dummy indicating household tribe, and income(log) and Zi.
Statistical significance* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

nificant at 10 and 1 percent levels, respectively. Similarly, buying IBLI decreases both the intensity of conflict exposure (measured as the number of conflict deaths within 50 km) by about 0.42 and households' statistical risk of conflict exposure by about 2 percentage points (columns 3 and 4). Although highly variable in magnitude, these effect sizes are consistent in direction across measures and suggest that IBLI has a protective effect against conflict risk, independent of rangeland conditions.

While the impacts that we see for IBLI's direct effect are themselves intriguing, we

Table 4: Mediation Results

	(1)	(2)	(3)	(4)
	Self-reported conflict experience	ACLED within 50 km conflict exposure	Fatalities within 50 Km	Statistical risk of violence
Panel A: Equation (9)				
Predicted IBLI uptake	-0.095*	-0.181***	-0.418***	-0.017**
	(0.06)	(0.051)	(0.113)	(0.007)
zNDVI (LRLD)	-0.005**	-0.006***	-0.027***	-0.001***
	(0.002)	(0.001)	(0.005)	(0.000)
Panel B: Model parameters				
T on M (est. in Table 3)			-0.006***	
			(0.002)	
Z on M (est. in the first stage of Equ.9 or Table 3):			0.195***	
			(0.015)	
ACME	0.001	0.002	0.004	0.0002
TE (cal.: DE+ACME)	-0.005	-0.004	-0.023	-0.001
TE (est in Table 2):	-0.003	-0.005	-0.026	-0.001
Ratio of indirect to direct effect: LRLD	-0.20	-0.33	-0.15	-0.20
ACME as % of the TE: ACME/TE(cal.)	-20%	-50%	-17%	-20%
ACME % of the TE: ACME/TE(est.)	-33%	-40%	-15%	-20%
Mean of conflict(Never purchased IBLI)	0.33	0.08	0.12	0.25
Observations	1466	1466	1466	1466
Model F-stat	2.30	5.30	6.58	19.41
Underidentificationa	112.68	112.68	112.68	112.68
Weak identification	155.39	155.39	155.39	155.39
Overidentification (Sargan test, P-value)c	0.000	0.000	0.000	0.000

Note: Columns 1 and 2 report LPM estimates whereas columns 3 to 4 report OLS estimates of conflict exposure measures. Panel A presents second-stage results from estimating the mediation model using IBLI uptake (dummy=1 if a household purchased IBLI prior to the interview) as a mediator, M. Treatment represents LRLD zNDVI values prior to the purchase of IBLI product for LRLD season for the survey reference period and should be interpreted in the direction of green pasture. Panel B summarizes related model parameters and explains how they can be assessed. The TE can be estimated (est.) or calculated (cal.). To ease interpretation ACME uses IBLI uptake dummy if a household purchases IBLI during a survey reference period. Discrepancies between estd. and calc. in columns (2) to (4) are due to rounding errors, over-identification or due to the fixed residual variance of the logistic regression model (MacKinnon et al. (1993; 2007). All specifications include the full set of control variables, exactly as in as in Table 2, along with round and index-area fixed effects. Robust standard errors clustered at the household level are in parentheses.
Statistical significance* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

are, in this work, concerned with the interaction of drought shocks and conflict risks and the way IBLI may interdict in those linkages. Therefore, in Table 4, we also report the estimated ACME for IBLI participation. As described in section 5 this statistic is created by multiplying the direct effect of IBLI on conflict (discussed above) by the effect of rangeland conditions on IBLI uptake. We observe, across our outcomes, that the ACME is positive and statistically significant. As expected, in terms of magnitude, the reported statistics are smaller than the direct effect of rangeland conditions. While the positive sign on our ACME may imply that IBLI intake exacerbates conflict, we must draw attention to our earlier discussion of the rangeland condition-conflict link in section 6.1. As we expect conflict to be caused by deteriorated rangeland conditions, the key interpretation of our reported ACME statistics is that as rangeland conditions deteriorate, conflict risk increases. However, for households who participate in IBLI, that conflict risk increases less severely.

Depending on the type of conflict considered, the ACME suggests that IBLI uptake mediates between 17 percent and 40 percent of the link between rangeland conditions and conflict exposure. When we restrict our analysis to only consider insurance uptake for LRLD season, as we suggested in section 6.2, we see the indirect effect of IBLI uptake can mediate up to 50 percent of the total effect of rangeland condition on conflict exposure. The direct effect captures the effects of weather shock on conflict exposure that are not related to shock-induced IBLI uptake effects, such as agricultural productivity (bad harvest, loss of livelihoods) and forage availability, among others.

In summary, although we observed differences in terms of the magnitude of the estimates of IBLI uptake on the different measures of conflict exposure, our analysis clearly shows that IBLI coverage attenuates the effects of weather shocks on conflict among (agro-)pastoral households. By weakening the link between weather shocks and conflict exposure or directly affecting mobility, productivity, and herding behavior, IBLI coverage persistently reduces the risk and intensity of conflict exposure induced by drought shocks for insured households. As such, index insurance products such as IBLI, which are designed to protect against the negative consequences of droughts, may have unintended positive externalities on the households' conflict risk.

Throughout this analysis, we have considered our "treatment" variable to be the zNVDI measure of rangeland conditions. However, in reality, we expect pastoralist behavior to be sensitive to incidences of drought. As such, in appendix B, we present the results from our mediation analysis where we consider our treatment to be a binary variable reflecting drought[5] as well as using alternative rangeland measures discussed earlier. Our results suggest that the relationship suggested by the results in Table 4 is robust to the alternative

[5] As measured by the indemnity trigger for the IBLI contract

definitions of the treatment. As an additional insight, we find suggestive evidence that the conflict-attenuating effect of IBLI uptake is larger for intergroup conflict exposure (i.e., conflict with other ethnic groups).

7 Conclusion

Using household survey data associated with the pilot of a novel index insurance product, this paper has demonstrated three key relationships underlying the weather-conflict-social protection nexus. First, we have shown a link between weather shocks, proxied by rangeland conditions, and conflict risk. Although, within the context of southern Ethiopia, this link is variable across seasons. Second, we have demonstrated that previous weather experience is predictive of participation in index insurance programs. This may indicate a larger relationship between shock experiences and preferences for social protection participation. Finally, we have shown that for those who uptake index insurance due to weather experience, the link between weather and conflict risk is attenuated by up to 50 percent. This latter finding, compounded with the negative direct effect of IBLI participation on conflict risk, may suggest that IBLI has the potential to be an effective protective factor in fragile and conflict-affected settings.

Using a novel IV approach to causal mediation analysis, we find that IBLI uptake attenuates the effects of weather shocks on households' conflict exposure. Our results show that IBLI uptake leads to decreased conflict risk and that coverage interdicts in the causal link between drought occurrence and conflict exposure during coverage. Depending on the measure of conflict considered, we find that IBLI uptake has the potential to reduce approximately between 17 and 50 percent of the total effects of drought shocks on conflict exposure. Additionally, we find that IBLI has a potentially large direct effect on conflict exposure. Here, our estimates are varied in size across measures (a 1.7 percentage point decrease in statistical conflict risk vs. an 18 percentage point decrease in conflict within 50 km) but consistently display a negative impact on the risk of conflict exposure.

At the start of this work, we explored various potential mechanisms underlying the results we observe. In multiple ways, IBLI is likely to increase household resilience and reduce reliance on coping strategies such as satellite grazing or asset selloff (Toth, 2015). These effects have likely reduce the incentive or need to raid and reduce frictions that could lead to inter-group disputes. Another possibility would be that improved productivity and herd shrinkage reduces the pressure on rangelands and competition over resources. It is also possible that IBLI coverage changes the herding strategies of pastoralists in ways that reduce grazing pressure, which in turn can lower both occurrence and intensity of the conflict. We observed in our data that IBLI reduces both the likelihood of household members' migration intentions and the likelihood of making early herd migration from base camp to satellite grazing sites during droughts where most of the conflicts occur Toth et al. (2019). Unfortunately, potentially the largest limitation of this work is that we are unable to disentangle these causal mechanisms. Answering these questions would require further research.

Additionally, We must note that the measured effects of rangeland conditions on conflict exposure that we observe are reasonably small. We surmise that two main factors can explain what we believe are attenuated effect sizes. First, in this setting, pastoralists are more likely to face low-intensity conflict as a result of property disputes than large-scale armed conflict. In these cases, ACLED is likely to underreport incidences due to its reliance on journalism for data collection. This means our outcome variables associated with the ACLED data are likely to be an underestimation of the true conflict prevalence. Second, while we cluster our standard errors throughout our analysis at the index level to match the level at which discount coupons are randomly assigned, the spacial construction of our outcome variable using ACLED data would naturally imply that there is spatial correlation between households in terms of conflict exposure. As such it is unclear whether we have properly accounted for inter-group correlations through the clustering of our errors. Further, it is unclear what level of clustering would ameliorate this issue. Even for our self-reported measures, there are likely to be significant within-group correlations that we are unable to account for.

IBLI has been developed and widely promoted in southern Ethiopia to protect pastoral households from the impacts of drought by making indemnity payouts based on satellite readings of the rangelands. At the same time, this paper has shown that IBLI rolled out can contribute to act as a protective factor against conflict and potentially attenuate the weather-conflict link. In this way, our findings justify allocating spending earmarked for peacekeeping toward establishing social protection programs in areas with complex conflict-weather risk profiles.

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A Appendix A: Variable Construction

A.1 Weather shocks

Although many studies capture weather shocks using various methods, we prefer to use the index that is used by the IBLI product to assess relative rangeland conditions. Specifically, for each 10-day NDVI observation, the NDVI are averaged across the index area unit level (see Figure 1 for the classification of index areas). Those 10-day averages are then averaged over the season in questions to provide a single value for each index unit in each season. This process has been performed across all observed seasons in the data set so that an anomaly index can then be generated by subtracting the index unit mean of this index across all seasons and dividing that difference by the index unit standard deviation of that index to

Table A1: Variable Construction

Variable	Description	Ethiopia		
		Mean	Stand Dev	N
Household Characteristics				
Female	Head of household is female.	0.21	0.41	2047
Age of HH	Age of head of household, in years.	51.24	18.16	2047
Married	Head of household is a widow.	51.24	18.16	2047
Education	Education level of household head, in complete years	0.85	0.36	2048
TAE	The sum of household members' in adult equivalence (AE) where AE is determined by the following: AE=0.5 if age<5, AE=0.7 if 4<age<16 or age>60, AE=1 if 15<age<61.	0.64	1.96	2047
Religion	Religion of household head is traditional	3.61	1.6	2047
Herd size	Sum of livestock owned by the households in TLU where 1 TLU=0.7 camels=1 cattle=10 sheep=10 goats.	18.85	28.22	2047
#donkey owned	Total # of donkey owned by household	0.86	1.54	2045
# poultry owned	Total # of poultry owned by household	2.44	4.32	2045
Livestock mortality	Total number of livestock that died in that season divided by the total number of livestock owned in that season.	3.31	9.44	2047
Self-help group	1 if household is a member of self-help group	1.94	0.24	2046
Other variables				
Wealth index	Wealth index generated using PCA	0.02	1.85	2047
Income	Average annual real income per adult equivalent in Kenyan shillings (KSH, February 2009) or Ethiopian Birr (ETB, February 2012)	10496.96	28568.46	1973
Net transfer	The difference between total transfer received and given out, excluding cash transfers by the program	278.79	2820.62	2048
Hours to camp	Livestock move from base camp to any water point outside the village	0.46	0.5	2047
Off-take	1 if household have livestock off-take between October and September last year	1.19	2.36	1786
Farm land	Household owns farmland	0.72	0.45	2047
Irrigated land	Total irrigated land in hectares	0.02	0.17	2047
Off-farm employment	A dummy variable indicating 1 if any household member participates in off-farm activities	0.31	0.46	2047
Migration	A dummy indicating 1 if household has migrant members	0.75	0.43	2047
Treatment				
CZNDVI-LRLD	Cumulative ZNDVI for LRLD	-3.71	10.33	2047
CZNDVI-SRSD	Cumulative ZNDVI for LRLD	3.33	5.26	2047
Mediator				
IBLI	1 if a household purchased IBLI coverage in the current season	0.25	0.44	2048
TLU insured	Total number of IBLI coverage purchased (in TLU)	0.7	3.182	2047
IV variables				
Coupon	A dummy variable that takes 1 if a household received discount coupons	0.7	0.8	2047
Audio tape	1 if a household received a randomly assigned extension treatments in audio tape or comic book	0.02	0.14	2047
Comic book	1 if a household received a randomly assigned extension treatments in comic book	0.04	0.2	2047
Outcome variables				
Conflict experience	Household lost animals due to conflict (TLU)	1.04	3.74	2047
Household self-reported concern or risk is insecurity/violence/fights	Insecurity/violence/fights has been reported as top 3 major concerns or risks to a household (1=yes)			
Household experienced Raiding/Conflict	Household experienced raiding/conflict (1=yes) during the last 12 months prior to the survey	0.32	0.47	2048
ACLED Within 50km conflict exposure	Conflict exposure within 50km (1=yes) based on ACLED dataset	0.07	0.25	2047
ACLED Within 50km fatalities	Number of fatalities within 50km based on ACLED dataset	0.1	0.55	2047
Perceived risk of conflict	Predicted perceived risk (probability)	0.32	0.24	2023
Off-farm employment	A dummy variable indicating 1 if any household member participates in off-farm activities	0.31	0.46	2047
Migration	A dummy indicating 1 if household has migrant members	0.75	0.43	2047

estimate relative seasonal forage condition per unit (Vrieling et al., 2016b). In addition to its use as the IBLI index, this type of standardized cumulative NDVI (zNDVI) has been used in many circumstances to track relative forage conditions.

The czNDVI anomaly is computed for each index unit (at woreda or county level) and for each agricultural season (i.e. for both long rain long dry and short rain short dry seasons), so that it is computed twice per year. In a causal mediation framework, forage conditions before IBLI sales periods influence household decisions regarding IBLI purchase. Accordingly, at least two zNDVI observations before IBLI sales periods are considered relevant zNDVI values influencing purchases, i.e., LRLD zNDVI and SRSD zNDVI values preceding each IBLI sales period. Since the index has spatial and temporal features (computed independently for the administrative areas), we are able to associated each geo-referenced survey household to and index unit and therefore indicator of drought.

Although one can maximize the exogenous variations in these localized droughts as well as its temporal heterogeneity, one limitation would be the possibility of limited spatial heterogeneity across these lowest administration levels as well as individual experience. To account for this and as a robustness checks we use various alternative measures of rangeland conditions such as enhanced vegetation index (EVI), modified soil adjusted vegetation index (MSAVI), and precipitation, all a remotely sensed rangeland health measurement.

A.2 IBLI take-up

The mediation effect of IBLI coverage depends on the duration of the contract (in this case one year), sales windows during the survey reference periods (i.e. two sales periods in each survey round), and the time lag it takes to induce behavioral change after IBLI is lapsed. As indicated in Figure 1, although insurance coverage lasts for one year, and there are two sales periods in each survey round, there could be up to three relevant IBLI active policies that could affect households' likelihood of conflict outcomes. Therefore, our measure of IBLI coverage over the survey period (t) relevant for our mediation framework is the insurance take-up, which is insurance take-up policies over the three recent consecutive sales season prior to the survey. For instance, during the third survey round, policies purchased during the August-September 2012 sales season, policies purchased during the January-February 2013 sales season, and policies purchased during August-September 2013 sales season are active, so that the household would continue to maintain overlapping policies. Hence, they are all relevant and can affect households' likelihood of participating in violent activities. Previous evaluations using the Kenya dataset also suggest that the program participation effects last longer than a contract period (Jensen et al., 2017). For details of the construction of IBLI indices, zNDVI data set, and extrapolation method see (Vrieling et al., 2016b).

A.3 Exposure to conflict

Conflict here refers to non-state armed conflict, and other collective violence such as riots or disputes, communal violence and other social conflicts. Since pastoral conflict is more likely linked to weather shocks than armed conflict, ACLED data may under report the conflict incidents of interest. Hence, we do not differentiate between armed conflict and small-scale conflicts our conflict measure give more emphasis to such low-level violence due to the nature and focus of our study sites. Other measure of conflict would serve as an alternative and for robust checks.

Our choice of 50 km buffer zones is motivated based on the following reasons. There are several reasons supporting our choice for 50 km buffer zones. First, family and/or communal grazing land are not necessarily in the vicinity of a household. A study on cattle movement behavior and resource selection patterns based on integration of GPS-tracking of cattle herds and field observations in Borena zone, one of our study sites, suggest that the extent of movement ranged from 20 km^2 to 116 km^2 (Liao et al., 2017). Hence the choice of 20 km and 50 km-radius buffer zones is reasonable. Other studies document over 100 km as a maximum distance travel between base and travel movement destination to access pasture and water (Young, Sulieman, Behnke, and Cormack, Young et al.). Thus, the use of these buffer sizes combined with the fact that conflict sometimes spillover to neighboring counties or woredas, justifies the use of 20 and 50 km buffer sizes. Furthermore, smaller (higher) cutoff zones tend to limit (overstretch) the sample of affected households makes it difficult to detect any effects. Moreover, these studies suggest that cattle movement in search of resources varied by cattle type, forage availability, and season making it difficult to stick to a single buffer size.

B Appendix B: Robustness Checks

B.1 Drought as Treatment

We run various robustness checks to examine whether our results are robust to various definitions of treatment, alternative measure of mediator, potential violations of sequential ignorability assumption and specifications. As a first robustness check, we reconstructed our continuous treatment variable, LRLD and SRSD zNDVI before IBLI sales period, into a dummy variable. In doing so a household i in an index area a experiencing drought in LRLD or SRSD season in year t-1 is assigned a value of 1 if z-score falls below trigger (z =-0.842) (Equ. 11) or exit (z = -2.326) levels (Equ. 12). Whereas the trigger level refers to the the z-score threshold level below which the insurance starts to pay, exit refers to the z-score level corresponding to maximum payment, which is 100 percent (Vrieling et al., 2016a). These two thresholds are used to remain consistent with IBLI's current implementation policy in contract design and payout.

Where s refers to either LRLD or SRSD season preceding IBLI sales period, t-1 refers to the survey year prior to IBLI sales period and is in line with IBLI calendar. Results from these analyses are presented in Table B1. The estimates of our TE and ACME remain qualitatively similar for most of the conflict measures, suggesting that our previous results are robust to our definition of T. As an additional insight, we find suggestive evidence that the conflict-attenuating effect of IBLI uptake is larger for actual intergroup conflict than for household self-reported fear of exposure to conflict or perceived risk of conflict. In addition, we find that there is heterogeneous effects of droughts on both likelihood of buying IBLI policy and risk of conflict, depending on whether the drought occur during LRLD or SRSD season.

Table B1: Mediation using Drought Trigger as Treatment

	(1) Self-reported conflict experience	(2) ACLED within 50 km conflict exposure	(3) Fatalities within 50 Km	(4) Perceived risk of conflict: predation
Panel A: Estimation of Equ (9)				
Predicted IBLI uptake:	-0.04	-0.123**	-0.295***	-0.010*
	(0.082)	(0.048)	(0.102)	(0.006)
Triger: LRLD Drought dummy	-0.179***	-0.011	0.099***	-0.004
	(0.03)	(0.02)	(0.03)	(0.003)
Triger: SRSD Drought dummy	0.051	-0.017	-0.274***	-0.018***
	(0.034)	(0.038)	(0.035)	(0.003)
Panel B: Model parameters				
T on M: Drought LRLD	0.115***			
	(0.0333)			
T on M: Drought SRSD	-0.112***			
	(0.0366)			
ACME	-0.005	-0.015	-0.04	-0.002
F-joint test: ACME				
TE_LRLD (cal.: DE1+ACME)	-0.184	-0.026	0.059	0.006
Mediation effect as % of the TE: ACME/TE(cal.)	3%	57%	67%	33%
Observations	1466	1466	1466	1466
Number of households	515	515	515	515
Model F-stat	4.659	4.566	4.721	18.694
Underidentification	118.58	118.58	118.58	118.58
Weak identification	166.04	166.04	166.04	166.04
Overidentification (Sargan test, P-value)	0.000	0.000	0.000	0.000

Note: In all the models we control for round FE and Index area FE except for ACLED 50km. Trigger: LRLD Drought T is a defined as dummy taking a value of 1 if zNDVI $\leq$ -0.842; 0 otherwise. We find similar results using exit. In all the specifications, the same controls exactly as in Table 4 used. Robust standard errors clustered at the household level are in parentheses.
Statistical significance* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

B.2 Alternative Rangeland Measures

We also extended the analysis by analyzing the impacts of weather shocks on conflict exposure using Landsat-derived datasets of land cover and vegetation fractional cover of East Africa landscapes, an alternative detailed measure of east African rangelands data product to date. For this exercise, we use enhanced vegetation index, modified soil-adjusted vegetation index and precipitation indices as an alternative proxy to weather shocks, and explore their relationships with the five measures of conflict exposure. Doing so helps to ensure if our measure of weather shocks using zNDVI might be obscured due to spatio-temporal changes in rangeland conditions. Once again, the results for ACME are qualitatively in line with our base line treatment definition, i.e., zNDVI values (Table B2).

Table B2: Mediation using Alternative Rangeland Measures

	(1)	(2)	(3)	(4)
	Self-reported conflict experience	ACLED within 50 km conflict exposure	Fatalities within 50 Km	Statistical risk of violence
Panel A: using EVI as T				
Predicted IBLI uptake	-0.077	-0.127***	-0.268***	-0.011*
	(0.081)	(0.047)	(0.099)	(0.006)
Lagged LRLD EVI	1.014**	-0.477***	2.584***	0.210***
	(0.408)	(0.17)	(0.445)	(0.031)
T on M		-0.721*		
		-0.439		
ACME	-0.06	-0.092	-0.193	-0.008
Observations	1466	1466	1466	1466
Number of households	515	515	515	515
Model F-stat	2.222	4.589	4.586	20.832
Underidentification	123.44	123.44	123.44	123.44
Weak identification	175.57	175.57	175.57	175.57
Overidentification (Sargan test, P-value)	0.000	0.000	0.000	0.000
Panel B: using MSAVI as T				
IBLI uptake	-0.067	-0.120**	-0.266***	-0.011*
	(0.081)	(0.047)	(0.099)	(0.006)
Lagged LRLD MSAVI	1.650***	0.335	-1.293***	-0.110***
	(0.453)	(0.215)	(0.324)	(0.033)
T on M		-0.847*		
		(0.466)		
ACME	-0.057	-0.102	-0.225	-0.009
Observations	1466	1466	1466	1466
Number of households	515	515	515	515
Model F-stat	2.514	4.98	3.984	19.972
Underidentification	122.97	122.97	122.97	122.97
Weak identification	174.65	174.65	174.65	174.65
Overidentification (Sargan test, P-value)	0.000	0.000	0.000	0.000

Note: EVI (Enhanced Vegetation Index); MSAVI means Modified Soil-Adjusted Index. The same controls used as in Table 4. Robust standard errors clustered at the household level are in parentheses. Statistical significance* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.