The Environmental Impacts of Microfinance: Index-Based Livestock Insurance and East African Rangelands

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Abstract

Expanded access to financial products has ambiguous effects on natural resources use, especially in environments lacking clear private property rights. Index-based livestock insurance (IBLI) is a micro-insurance product originally developed to help pastoralists in northern Kenya and southern Ethiopia manage catastrophic drought risk. Rigorous impact evaluations have clearly established welfare and productivity gains from IBLI. Open questions remain, however, regarding IBLI's potential environmental impacts, especially given the region's predominantly communal land tenure systems. Might IBLI encourage overstocking or change grazing behaviors that harm the rangeland systems on which pastoralists rely, ultimately undermining the product's effectiveness in reducing livestock mortality risk? Or does IBLI reduce precautionary savings in-kind, thereby reducing overstocking and improving rangeland health? We address this question empirically by combining administrative data on the roll-out of IBLI with remotely-sensed rangeland quality measures across an area spanning approximately 643,000 km^2 over the period 2000-2020. Using a staggered differences-in-differences estimator we find evidence for neutral to positive impacts of IBLI on East African rangelands.

Keywords: microfinance, drought, rangelands, pastoralism, remote sensing

JEL classification: O16, O13, Q24, C23

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1 Introduction

Recent decades have witnessed a microfinance revolution aimed at empowering the poor to save, borrow, and insure so that they can invest in sustainable improvements in living standards (Besley 1995; Robinson 2001). A sizeable literature documents generally favorable impacts of microfinance interventions on incomes, investment and other indicators of human well-being (for reviews, see Van Rooyen, Stewart, and De Wet 2012 and Cull and Morduch 2018).

Far less attention has been paid to whether improved access to financial products might generate unintended negative impacts on the natural systems that disproportionately support the livelihoods of the rural poor. Improved access to financial services could boost investments that expand or intensify extractive operations, with plausibly adverse impacts on forest, land, water and/or wildlife resources, especially in settings where property rights are insecure or open access tenure prevails (Assunção et al. 2020; Noack and Costello 2024). Conversely, newfound access to financial services could facilitate environmentally favorable changes, for example by enabling sustainable agricultural intensification that reduces extensification into fragile ecosystems, supporting transitions out of natural resource extraction industries, or reducing risk management behaviors that degrade nature (Barrett 1999; Wilcox, Just, and Ortiz-Bobea 2025). Indeed, Noack and Costello (2024) show that in global fisheries, credit market development increases resource extraction under insecure property rights but reduces resource extraction under secure property rights. Such findings illustrate that the environmental impacts of microfinance are analytically ambiguous, sensitive to local conditions, and can be globally important.

The scant evidence on this topic originates partly from the paucity of data that reliably link microfinance interventions and environmental outcomes, and partly due to the small spatial scale and short duration of most microfinance interventions. While two recent studies (Assunção et al. 2020; Noack and Costello 2024) have overcome these barriers in regards to fisheries and forests, we know of no evidence with respect to rangelands, the dominant land type on Earth, nor on microinsurance.

Index-based insurance, a form of microfinance, has been widely promoted in low-income, rural settings where adverse selection, moral hazard and high transaction costs limit access to conventional indemnity insurance (Carter et al. 2017; Jensen and Barrett 2017). Many index insurance products have generated favorable outcomes for policyholders, including increased incomes, productivity, subjective well-being or children's education, as well as reduced conflict, distress sales and meal skipping (Karlan et al. 2014; Jensen, Barrett, and Mude 2017; Janzen and Carter 2019; Tafere, Barrett, and Lentz 2019; Janzen and Carter 2019; Stoeffler et al. 2022; Barrett et al. 2025; Gehring and Schaudt 2024; Jensen et al. 2025; Sakketa, Maggio, and McPeak 2025).

Given rural livelihoods' heavy reliance on natural resources, however, the sustainability of any observed gains from index insurance – or any microfinance product – depends in part on avoidance of unintended, negative environmental externalities. Multiple candidate mechanisms might cause environmental spillovers from index insurance uptake. For example, by increasing risk-adjusted returns, an index insurance product might encourage expansion of the cultivated frontier or grazing lands into fragile areas, resulting in loss of natural habitats, e.g. forests, protected areas, wetlands etc. Index insurance might also encourage more intensive production on existing working lands, perhaps via reduced mobility and intensified local grazing, or general overstocking and overgrazing of rangelands, leading to rangeland degradation, erosion, or soil nutrient loss, etc. But the provision of formal, financial insurance could reduce environmentally-damaging self-insurance behaviors, such as precautionary savings 'on the hoof' that result in overgrazing (Jensen, Barrett, and Mude 2017; Cissé and Barrett 2018; Bulte and Haagsma 2021) or overuse of natural resources as a means of self-insuring against producer price risk (Barrett 1999; Wilcox, Just, and Ortiz-Bobea 2025). The net environmental impacts of index insurance are therefore analytically ambiguous and an open empirical question (Bhattacharya and Osgood 2014).[1]

This paper examines the environmental impacts of long-term access to index insurance. It does so by exploiting a new, high spatial resolution data set from 2000-2020 that covers 745,840 km^2 of East African rangelands that span the gradual roll-out of a successful micro-insurance product, index-based livestock insurance (IBLI). IBLI has now insured more than 3.2 million livestock herders in Ethiopia and Kenya against catastrophic drought losses, including through the Kenyan government's national Kenya Livestock Insurance Program (KLIP, Jensen et al. 2024) and the World Bank-led De-risking, Inclusion, and Value Enhancement of Pastoral Economies in the Horn of Africa (DRIVE) project (https://zep-re.com/drive-project/about-drive/). The spatial and temporal scale of IBLI's diffusion across southern Ethiopia and northern Kenya, combined with high spatial resolution data on rangeland conditions spanning IBLI's pre- and post-introduction periods, enable rigorous causal identification of microfinance's impacts at scale on a key natural resource. As best as we can tell, no comparable empirical assessment exists.

IBLI offers an uncommon opportunity to test for microfinance's impacts on the natural environment. IBLI introduced drought insurance to low-income pastoralists who graze livestock on East Africa's rangelands, where drought-related herd mortality is the primary source of wealth loss (Lybbert et al. 2004; Barrett et al. 2006; Santos and Barrett 2011; Chantarat et al. 2013; Toth 2015; Santos and Barrett 2019). Initially piloted in northern Kenya in 2010, IBLI expanded into southern Ethiopia in 2012, and subsequently across northern, eastern and central Kenya (Jensen et al. 2024). Several impact evaluations have demonstrated IBLI's benefits, including improved livestock productivity, children's nutritional status and educational attainment, household income and subjective well-being, and reduced conflict and adverse coping strategies, among others (Jensen, Barrett, and Mude

[1] Prior research on finance's environmental impacts includes Walters et al. (2012) and Smith and Goodwin (2013) on the impacts of crop insurance programs in the United States, Feng, Han, and Qiu (2021) on reductions in pesticide use in China, impacts on global fisheries that depend on the security of marine property rights (Noack and Costello 2024), and decreased deforestation in Brazil stemming from expanding rural credit, conditional on land titling and environmental regulation compliance (Assunção et al. 2020).

2017, Janzen and Carter 2019, Tafere, Barrett, and Lentz 2019; Barrett et al. 2025; Gehring and Schaudt 2024; Jensen et al. 2025; Sakketa, Maggio, and McPeak 2025). But if IBLI adversely affects rangelands, it might ultimately cause the very herd losses against which it ostensibly insures.

Theory- and simulation-based studies predicted IBLI might have negative impacts on rangelands, but relied on strong, untested assumptions (John et al. 2019; Bulte and Haagsma 2021). Empirical findings suggest that IBLI reduced in-kind precautionary savings in the form of livestock and reduced trekking distances, either of which could have positive or negative environmental impacts (Jensen and Barrett 2017; Toth et al. 2020). So the question remains unsettled.

We use the aforementioned new data set of remotely-sensed rangeland quality indicators from 2000-2020 (Soto et al. 2024) and administrative data on the staggered roll-out of IBLI across Kenya and southern Ethiopia from 2010-2020 to estimate IBLI's environmental impacts across approximately 643,000 km^2. We tap recent advances in differences-in-differences (DiD) estimation in settings with effectively-random, staggered roll-out and potentially-heterogeneous treatment effects while controlling for pre- and post-treatment variation in exogenous covariates (Roth et al. 2023; Gardner et al. 2025).[2] In our setting, it is crucial to control for pre- and post-treatment seasonal weather variation to credibly isolate the effect of IBLI from other processes that may drive much of the observed variation in rangeland conditions (Purevjav et al. 2025).

We estimate models at multiple spatial scales and account for herder movement by inverse distance weighting IBLI exposure within a neighborhood defined by GPS-tracking of livestock migration in the study area (Liao et al. 2018). Across a series of rangeland health indicators (described in Section 3), we find no evidence of negative rangeland quality impacts from IBLI. On the contrary, IBLI's environmental impacts range from neutral to statistically

[2]The Borusyak, Jaravel, and Spiess (2024) estimator generates estimated treatment effects numerically equivalent to those of Gardner et al. (2025).

significantly positive. At the extensive margin, we find mostly precisely-estimated null results with the exception of small but statistically significant increases in biological productivity indicators (e.g., reflectance-based enhanced vegetation indices). At the intensive margin, not only do vegetation indices increase significantly with increased IBLI exposure but so does the fraction of land cover in photosynthetic vegetation, while we still get precise null effects on both bare ground and non-photosynthetic vegetation cover.

The rest of the paper proceeds as follows. Section 2 provides an overview of East Africa pastoralism and IBLI, the administrative data on IBLI's expansion, our approach to measuring IBLI exposure across space and time, and a summary of trends in IBLI uptake. Section 3 discusses the rangeland quality measures, along with trends in the study area, and covariates used to control for ambient natural processes. Section 4 presents the econometric strategy for causal identification of IBLI's impacts on rangeland quality indicators. Section 5 presents results and Section 6 concludes.

2 Empirical Setting and IBLI Exposure

2.1 East African Pastoralism and IBLI

The arid and semi-arid lands (ASALs) of East Africa are characterized by limited physical and institutional infrastructure and low human population densities. Combined with poor soils and low and variable rainfall, the main livelihood is pastoralism, the extensive grazing of livestock on communal lands with complex, contested property rights (McCarthy et al. 1999; McPeak, Little, and Doss 2011). Livestock are pastoralists' main store of wealth and generate most of their income, social status, and nutrient intake.[3] Livestock productivity depends fundamentally on rangeland conditions, which is adversely affected by overgrazing. Garrett Hardin used extensive livestock grazing to motivate his 'tragedy of the commons'

[3] See McPeak, Little, and Doss (2011) or Jensen et al. (2024) for rich descriptions of this area.

hypothesis.[4] Pastoralists in the region have historically used mobility to manage drought risk exposure by adjusting seasonal and daily movements in response to drought-induced impacts to forage quality and quantity, though in the modern era a variety of factors are working to reduce herder mobility. Any intervention that might change pastoralists' investment in livestock or their grazing patterns could therefore plausibly affect rangelands.

IBLI was originally designed to help pastoralists in this region rebuild their herds after catastrophic drought events.[5] Pastoralists can buy IBLI policies specific to the 'index insurance unit' (IU) - approximately equivalent to a sub-county in today's Kenya - in which they principally reside (Figure 1). IU-specific premium rates and indemnity payments are based on historical and current realizations of normalized difference vegetation index (NDVI) data generated from moderate resolution imaging spectroradiometer (MODIS) satellite imagery in near-real-time by the US government's National Oceanic and Atmospheric Administration. IBLI contracts last 12 months and are sold during each of two semi-annual sales periods, in January-February and in August-September. That timing reflects the bimodal rainfall patterns of the region, with a long rainy season that typically runs March-June followed by a long dry season that lasts through September, then a weaker, short rainy season that runs October-December, followed by the January-February short dry season. When the NDVI-based index falls beneath a contractually-specified seasonal trigger - originally calibrated to reflect a 15 percent expected loss (Chantarat et al. 2013) - policyholders receive a cash payout.

IBLI was piloted in Marsabit District of northern Kenya in January 2010. After IBLI worked as designed during a major drought in 2011, a very similar IBLI product was introduced into the neighboring Borana region of southern Ethiopia in August 2012. Subsequently, IBLI incrementally rolled-out into other parts of the Kenyan ASALs, with new commercial underwriters taking up the product, and to additional kebeles (the smallest administrative

[4] Hardin (1968), p.1244 wrote "The tragedy of the commons develops in this way. Picture a pasture open to all. It is to be expected that each herdsman will try to keep as many cattle as possible on the commons."

[5] See Jensen et al. (2024) for details on the development, adaptation, and expansion of IBLI.

unit in Ethiopia) within the Borana Zone of Ethiopia. In 2015, the Kenyan government launched the Kenya Livestock Insurance Program (KLIP), a state-subsidized purchase of IBLI on behalf of qualified, low-income herders. By 2018, IBLI was available for purchase in every IU shown in Figure 1, and by 2020 KLIP was present in all IUs in Kenya.

The timing and order of IBLI's roll-out across IUs was unrelated to rangeland conditions, driven chiefly by the operational capacity of insurance underwriters, their retail sales agents, and regulators (Johnson et al. 2019; Jensen et al. 2024). This generates plausible exogeneity in the timing of rangelands exposure to IBLI at the extensive margin, enabling evaluation of microinsurance's impacts on rangeland health. Exposure at the intensive margin has almost surely been endogenous to rangeland conditions that affect pastoralists' demand for IBLI (Jensen, Mude, and Barrett 2018). We discuss in Section 4 how we deal with that prospective endogeneity at the intensive margin.

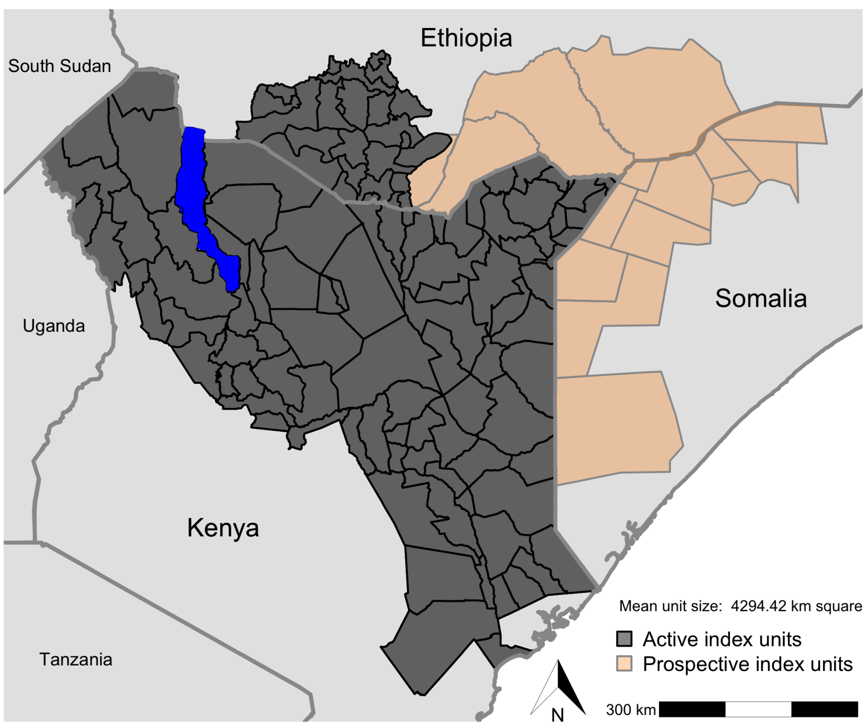

Figure 1: Active IUs span the northern and eastern portions of Kenya, and part of southern Ethiopia. Their boundaries are outlined and the area shaded grey. Prospective IUs in which IBLI was not yet introduced during our study period provide plausible control units and are shaded orange (in southern Ethiopia and western Somalia).

We identify plausible control areas in ASALs with very similar vegetation, climate, land-use and ethnic groups that border the IUs where IBLI was sold during the study period (Figure 1). These prospective IUs were identified and studied by the research team that developed and adapted IBLI during its expansion for the purpose of enabling introduction of IBLI there as well (Jensen et al. 2024). But for supply-side reasons related largely to underwriters' pre-existing coverage, the cost of initial produce design, and staffing, IBLI was not offered in those regions by 2020. IBLI is now expanding into those plausible control areas, however, under a large, World Bank-led, multi-country expansion under the De-risking, Inclusion and Value Enhancement of Pastoral Economies in the Horn of Africa (DRIVE) project, which launched in 2022. So these prospective IUs offer suitable natural control sites for our purposes, as they are not-yet-treated areas testably comparable to the sites where IBLI rolled out over its first decade.

2.2 IBLI uptake over time

We measure IBLI exposure using administrative sales data from the insurance underwriters that sell IBLI. The data frequency is semi-annual, reflecting the March-September long rains and long dry (LRLD) and the October-February short rains and short dry (SRSD) seasons corresponding to the IBLI contracts. We construct a time series of IU-level exposure to IBLI in both binary (i.e., presence/absence, the extensive margin) and continuous (i.e., the intensive margin in tropical livestock units (TLUs) insured)[6] forms from 2000-2020. Since IBLI was first sold in January 2010, all 2000-2009 observations take value zero, representing the pre-exposure period.

Figure 2 shows IBLI's expansion in TLUs insured by year and season, divided between the amounts insured via private purchase versus purchase through KLIP. Juxtaposed against these trend lines is the rangeland area in km^2 exposed to IBLI by year and season as measured

[6]TLU is a standard measure of livestock that sums across species based on average metabolic weight. In our region of study, the weights are: 1 TLU = 1 cow = 0.7 camel = 10 sheep/goats. The average cumulative exposure was 521 TLUs over the 2010-20 period.

within IU boundaries. KLIP substantially expanded coverage overtime (Figure 2),[7] while private purchases of IBLI fluctuated substantially. We also see in figure 2 that the area exposed to IBLI starts to level-out around 2015. Appendix A.2 provides analogous two-way plots, which feature additional measures of rangeland area exposed by low and high forage quality rangeland types (Figure A.2.1), measures of the total number of policies (Figure A.2.2), cumulative TLUs and policies (Figure A.2.3), and an animation of IBLI coverage over space and time at the IU level (Figure A.2.4).

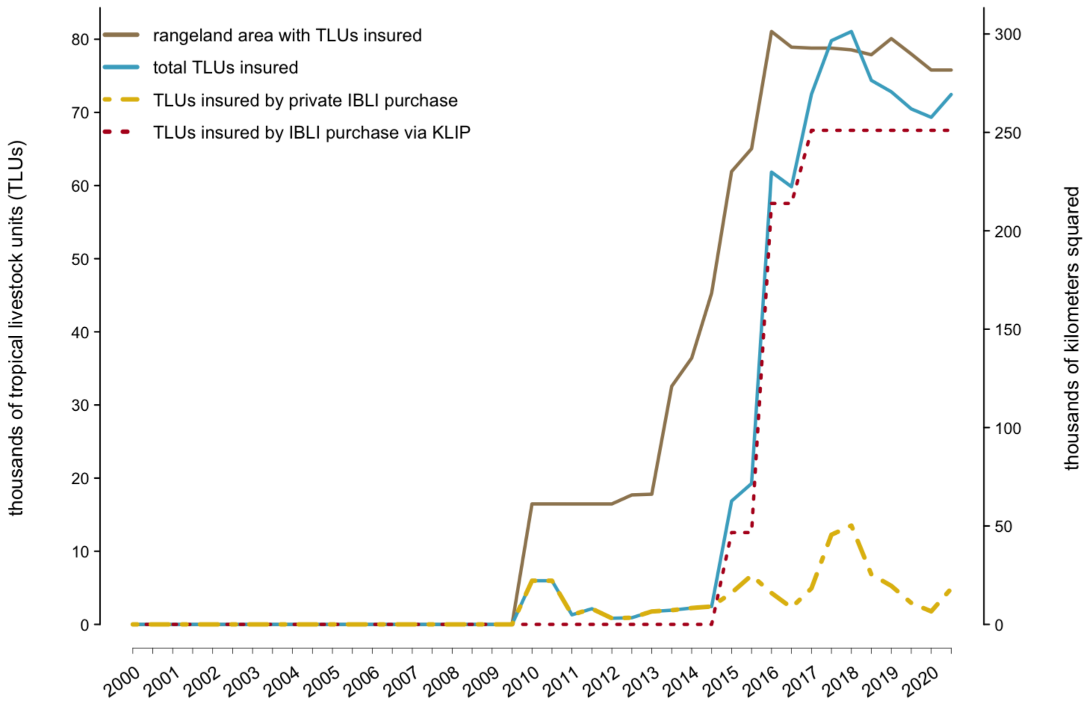

Figure 2: IBLI expansion in thousands of TLUs insured and area of rangelands exposed in thousands km^2.

2.3 Spatial units of analysis, herder movement, and IBLI exposure

In our study area, there are challenges to capturing meaningful variation in rangeland and herding processes and with measuring exposure to IBLI. One challenge comes with the fact that IUs are quite large while meaningful variation in rangeland quality (on this see more in

[7]The subsidy provided by KLIP is based on population. Once a local population received KLIP, it remains in place, hence the monotonic increase.

Section 3) and herding processes processes likely occurs at a smaller spatial scale. Another challenge comes with the potential for spillover effects from herders grazing across IUs. This is an issue because pastoralists regularly move their herds in search of forage and water (Coppock et al. 1994; Lybbert et al. 2004; Toth 2015; Jensen, Barrett, and Mude 2017). But unlike fully nomadic populations elsewhere, here herding is predominantly transhumant, organized around a permanent base camp, where some family members remain throughout the year, while other family members episodically trek herds to satellite camps where they stay for varying lengths of time depending on rangeland and biophysical conditions.

To address issues with scale, we study variation at four different levels of spatial aggregation. This approach also helps address trade-offs embodied in what geographers term the "modifiable areal unit problem" as it relates to prospective aggregation bias (Openshaw and Taylor 1979; Avelino, Baylis, and Honey-Rosés 2016). At the largest aggregate level we use IUs, and we also study sub-watershed unit levels 8, 9, and 12, also known as hydrologic unit codes (HUCs, hereafter, Lehner and Grill (2013)). Watersheds have geophysical boundaries set by the biophysical processes (e.g., hydrology, topography) that drive underlying rangeland ecosystems and grazing patterns, thereby offering natural spatial units of analysis for this study. The average size of these four resolutions in terms of area are: 4,294 km^2 (IUs), 739 km^2 (HUC 8), 263 km^2 (HUC 9), and 125 km^2 (HUC 12).

To account for potential spillover effects from herders grazing across IUs, we apply an inverse distance weighting (IDW) algorithm at the pixel level (30m), which accounts for exposure to IBLI within units (i.e., IU, HUCs) and within a surrounding neighborhood. To empirically ground neighborhood size we use data from GPS collars placed on livestock within pastoralists' herds in the Borana region of southern Ethiopia during 2011-2015 (Clark et al. 2006; Liao et al. 2017; Liao, Clark, and DeGloria 2018). Equation (1) defines the IBLI exposure variable of interest at the unit level that accounts for herder movement:

$$WIBE_i = IBE_i + \sum_{j^{-i}} \frac{(\mathbb{1}_j \ w_{ij})}{\sum\limits_{j^{-i}} \mathbb{1}_j \ w_{ij}} IBE_j \tag{1}$$

$WIBE_i$ represents the estimated weighted total IBLI exposure of unit i (i.e., IUs, HUCs) for a given time period (time and pixel-level summations are omitted for simplicity). IBE_i is the total rangeland-area weighted exposure (in TLUs insured) observed within spatial unit i for some year and season, w_{ij} is a weighting function that scales the observed rangeland-area weighted exposure within another unit $j \neq i$, and the indicator function $\mathbb{1}_j$ is a binary variable equal to 1 if unit j is within the pre-defined neighborhood of unit i. Weights are normalized such that $\sum_{j-i} \frac{\mathbb{1}_j \ w_{ij}}{\sum_{j-i} \ \mathbb{1}_j \ w_{ij}} = 1$.

We operationalize equation 1 using IDW for w_{ij}[8] and we use the aforementioned GPS livestock collar data to define a neighborhood distance for each unit for each of the aforementioned levels of aggregation. Specifically, we apply a neighborhood distance of 63 km, which reflects the sum of the mean and standard deviation of observed herding distances during each SRSD season over 2011-2015. This is a conservative distance as herding distances tend to be a bit larger in the SRSD. To weight adjacent exposure within this neighborhood for units $j \neq i$ we use a series of 9 evenly spaced (7 km) concentric buffers b_j emanating from the border of each unit i. To accomplish this, we down-scale IBLI exposure from IUs to Landsat-scale (30m) pixels via an 'all' rangelands mask (described in Section 3) since movement is likely to occur through all land types. Intersecting rangeland-area weighted IBLI exposure within each buffer is therefore weighted by the inverse of distance $b_j - (7\ km/2)$, which is the midway distance in meters between each buffer's inner and outer boundaries.[9] Appendix A.3 outlines our IDW algorithm in more detail and shows boxplots of grazing distances from livestock GPS collar data (Figures A.3.1), as well as graphical depictions of resulting neighborhood size and concentric buffers for a watershed unit near Lake Turkana (Figure A.3.2).

To study IBLI exposure we focus on cumulative TLUs insured at the extensive and

[8]Inverse distance weighting amounts to an application of a gravity model (Carrère, Mrázová, and Neary 2020) and has been used in spatial statistics and other studies of rangelands (Purevjav et al. 2025).

[9]For example, for any unit i the outside border of the farthest buffer b_9, is 63 km away from the border of unit i. Hence the sum of IBLI exposure within the intersecting pixels of the farthest buffer is weighted by the inverse of, 63 km - (7 km /2) = 59.5 km.

intensive margins and we study exposure as an irreversible state. Specifically, we consider a unit to be exposed to IBLI in the first period when cumulative $WIBE_i \geq 1$, so once one cumulative TLU is insured within a unit. Cumulative exposure accounts for the fact that any effects on rangelands are likely to be a function of the livestock units insured over time and the aggregate effects of herders' exposure to IBLI. Treating exposure as an irreversible state also accounts for the fact that there have been no disruptions to IBLI exposure during our study period.

In our staggered exposure estimation design (see details in Section 4), we take advantage of variation at the extensive and intensive margins by comparing exposed units to never-exposed and not-yet-exposed units. These comparisons include units located in areas in southern Ethiopia and western Somalia, which were not directly exposed to IBLI during our study period that are scheduled to receive IBLI coverage in the future. Figure 3 provides depictions of the number of exposed versus unexposed units at the HUC-12 level over time and provides contrasting counts with and without our IDW approach. The top panel of Figure 3 contrasts measures of extensive margin IBLI exposure at the HUC-12 level, with and without our IDW approach. The bottom panel shows the distribution of treated versus control units at increasing levels of intensive margin exposure using our IDW approach (e.g., $\geq$ 500 cumulative TLUs insured). These figures provide a clear visual depiction of how IDW increases the number of exposed units per period. At both the extensive and intensive margins, a large number of never-exposed and not-yet-exposed units are present in each period. The average level of inverse distance weighted cumulative exposure at the HUC-12 level over 2010-2020 was about 521 TLUs. Appendix 4 provides spatial animations at the HUC-12 level showing how our IDW approach impacts contemporaneous and cumulative IBLI exposure (Figures A.4.1-A.4.2), the cumulative distribution function of cumulative IDW exposure (Figure A.4.3), and a table of summary statistics on IBLI exposure over 2010-2020 for each level of aggregation (Table A.4.1).[10]

[10]Notably, portions of watershed units within prospective index units (where no IBLI sales have taken place during our study area) become exposed when we account for herder movement using IDW.

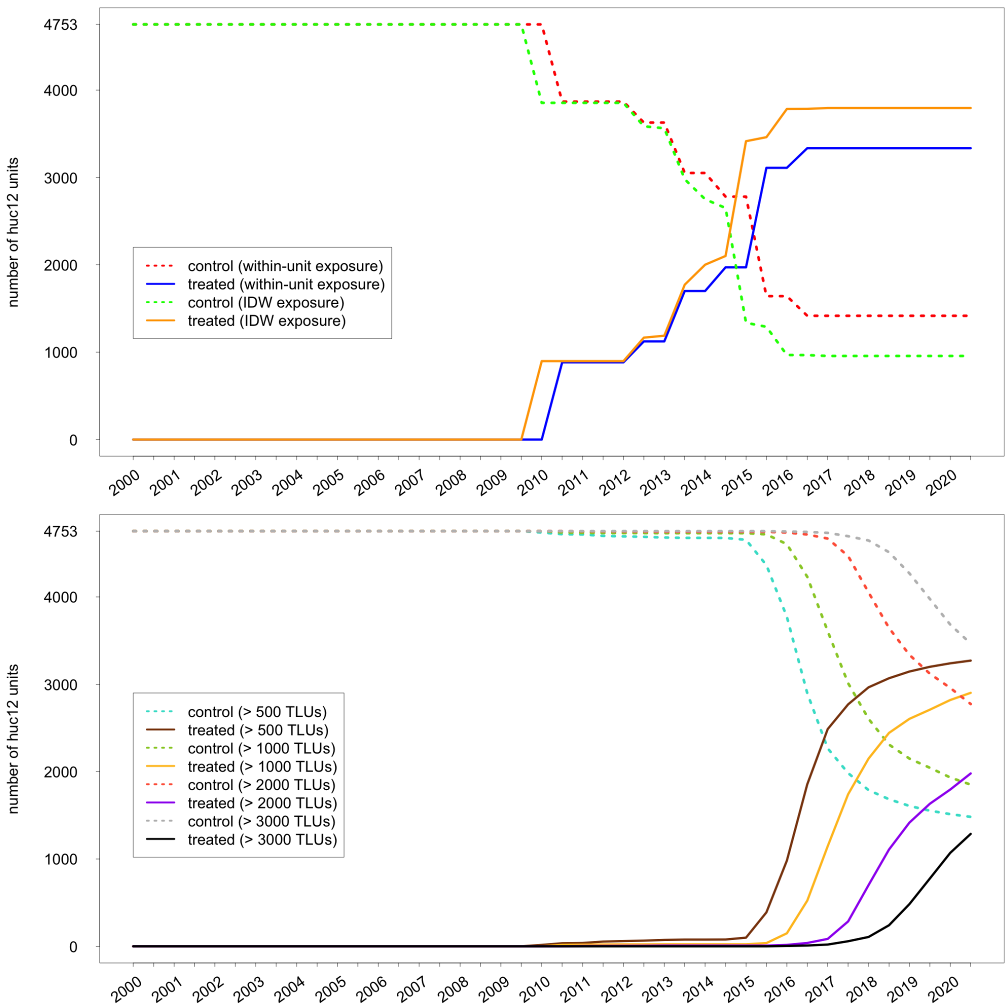

Figure 3: Top panel: Counts of extensive margin treated and control units over time at the HUC-12 level, contrasting contemporaneous IBLI exposure without IDW (within-unit exposure) and with IDW (IDW exposure). Bottom panel: Counts of treated and control units over time at the HUC-12 level for different intensive margins of exposure using IDW.

3 Rangeland Quality and Other Covariates

3.1 Rangeland Measurement and Data

No unique measure of rangeland quality exists; it is a latent variable. Rangeland scientists conceptualize "rangeland health" (RH) as a function of three primary attributes: biotic integrity, hydrologic function, and soil/site stability (Pellant et al. 2020). RH indicator measurement has historically relied heavily on field-based data collection. In much of the world, including our study area, available ground-based data are insufficient to answer research questions such as ours and collecting the needed data is cost-prohibitive. Remote sensing advances, however, now enable the development of validated RH indicators at scale (Reeves et al. 2015; Retallack et al. 2023).[11]

We use a combination of publicly available, remotely sensed data series and measures from a new multi-decadal high-resolution dataset on RH in East Africa that spans the entirety of our study area over the period 2000-2022 (Soto et al. 2024). These data include ten years of observations prior to IBLI's introduction and a similar duration post-introduction. By studying these series at the four aforementioned levels of aggregation (i.e., IU and HUC levels) we can recover meaningful variation in rangeland conditions over time and address potential aggregation bias from the modifiable areal unit problem (Openshaw and Taylor 1979; Avelino, Baylis, and Honey-Rosés 2016).

The dependent variables that we employ consist of fractional land cover measures and vegetation indices. For fractional land cover, we use the 30m series from Soto et al. (2024) that provide sub-pixel estimates of the proportion ($\in$[0,1]) of each pixel belonging to three classes: bare ground (BG), photosynthetic vegetation (PV), and non-photosynthetic vegetation (NPV). Due to high cloud cover in the region's LRLD season, these series are only available during the SRSD season each year. Generally speaking, more PV is desirable, more BG undesirable, and NPV can be neutral in that NPV offers limited forage value during the dry to wet season transition and can offer shade and help to reduce erosion and maintain soils and hydrology.

For vegetation indices, we use standard reflectance-based indices from publicly available 250m resolution MODIS data (Didan et al. 2021).[12] We favor the enhanced vegetation index (EVI), which is widely viewed as an improvement over other similar indices but we study

[11] Examples include work to characterize phenology and surface features like bare ground (Poitras et al. 2018; Wang et al. 2019; Rigge, Meyer, and Bunde 2021; Soto et al. 2024), measure woody shrub encroachment and state transitions (Liao, Clark, and DeGloria 2018), and model structural and site potential deviations and trends in fractional cover (Reeves and Baggett 2014; Rigge et al. 2019; Shi et al. 2022).

[12] Didan et al. (2021) rely construct 16-day composites of high quality daily MODIS imagery.

several for completeness.[13] These indices generally fall in the 0-1 range for vegetated surfaces, with values closer to 1 indicating higher levels of greenness and productivity. The advantage of MODIS-based indices, as opposed to Landsat, is that the shorter return interval mitigates data gaps from cloud contamination and sensor failure. As such, MODIS-based series offer more complete temporal and spatial coverage than the fractional land cover series and are available in the LRLD and SRSD.

To summarize these series in a meaningful way, we create aggregate fractional cover and vegetation measures within each areal unit using high resolution rangeland cover maps also developed by Soto et al. (2024). We use these maps to construct spatial masks, which we use as binary raster layers indicating usable pixels to capture important rangeland variation. Our main analysis relies on three spatial masks that permit study of potential heterogeneity across our study area: (i) an 'all' rangelands spatial mask that incorporates all rangeland types; (ii) a 'low' forage quality mask that reflects rangeland types with lower forage production potential for livestock; and (iii) a 'high' forage quality mask that reflects rangeland types with higher forage production potential for livestock.[14] Because year-to-year land cover can be susceptible to false state changes, and land cover change generally proceeds slowly in these systems, we use the modal land cover class over annually classified pixels for four five-year periods – 2000-2005, 2006-2010, 2011-2015, and 2016-2020 – and construct the all, low, and high masks for each period.[15] The final RH measures we employ are the proportion of each

[13]Additional series that we study include the Normalized Difference Vegetation Index (NDVI), the modified soil adjusted vegetation index (MSAVI), and near-infrared reflectance of vegetation (NIR_v). These series demonstrate very similar variation, so we focus our analysis on EVI.

[14]Soto et al. (2024) classify the following classes: closed canopy woodland (CCW), dense scrubland (DS), bushland (BU), open canopy woodland (OCW), sparse scrubland (SS), cultivated land (CL), grassland (GR), and sparsely vegetated land (SV). Every class is included in the 'all' group, including CL since agricultural land in the region is often grazed and difficult to distinguish from classes like GR. The 'low' quality group includes SV, BU, DS, and CCW. The 'high' quality group includes OCW, GR, SS, and CL.

[15]For example, to gather a summarized vegetation index at an areal unit level for high quality rangelands for 2006, we apply the 'high' rangeland mask for 2006-2010. See Appendix B.1 and Figures B.1.1 - B.1.3 for example maps of the mask layers used for these three definitions. Data used to construct each annual land cover layer span the most cloud-free period of the year, the SRSD season from October-February. Since rangeland state transitions infrequently occur at annual time-steps, land cover estimates generated from imagery data spanning the SRSD works well for capturing the state of the rangelands each year.

unit in each fractional cover class (BG, PV, NPV) and the mean vegetation index value for each time period and mask.[16] This combination of measures offers a credible approximation of important variation in RH at scale. Table B.2.1 in Appendix B.2 provides summary statistics on fractional cover measures and EVI by spatial mask (all, high, and low) and three specific rangeland type masks to highlight differences between rangeland types.

3.2 Other Covariates

Other time-varying natural processes impact RH and may be correlated with IBLI uptake. We therefore control for seasonal weather variation, which drives much variation in rangeland biological productivity in this region, as precipitation generates pulses in plant growth that attenuate over time and more rapidly with higher temperatures (Ellis and Swift 1988; Coughenour, Coppock, and Ellis 1990). For temperature data we construct binned temperature exposure variables using 9km resolution, hourly temperature data from the reanalysis ERA-Land5 product (Muñoz-Sabater et al. 2021). For precipitation, we use 5km resolution data from CHIRPS (Funk et al. 2015), which uses remotely sensed and ground based station data to construct spatially continuous measures of precipitation. Using data from CHIRPS we gather measures of the average and standard deviation of precipitation. Using these series, we construct control variables for each unit, year, season and level of aggregation over 2000-2020. Appendix B.2 provides summary statistics on these weather covariates (Table B.2.2).[17]

3.3 Trends in rangeland conditions

Figure 4 shows unconditional trends in the mean share of BG, PV, NPV, and EVI for all rangelands, along with the contemporaneous trend in average precipitation. Analogous figures in Appendix B.3 show the contrasting trends across all, low, and high forage quality

[16] Table B.1.1 in Appendix B.1 details how these measures relate to the RH framework and standard ground-based approaches to measuring RH attribute indicators.

[17] Fire also impacts RH. However, in this region fire can be intentionally set to achieve different management objectives making it endogenous with rangeland conditions and thus a bad control.

rangelands for fractional cover (Figure B.3.1) and EVI (Figure B.3.2). Figure 4 offers clear evidence of regular swings in the area share of BG, PV, and NPV that match closely with changes in precipitation. This is evident in 2006, 2011, and 2019, with notable increases in PV and decreases in BG and NPV. Likewise, a strong positive correlation between EVI and fluctuations in seasonal precipitation is also apparent. Moreover, the apparent neutral trend in EVI suggests that biological productivity has held fairly constant in our study region over our study period, though subject to periodic, large swings. The corresponding figures in Appendix B.3 do not show marked differences between high and low forage quality rangelands, though in fractional cover measures we do see support for our masking strategy in that we see the share of BG is generally higher than that of PV in the low forage quality rangelands group, and vice versa for high forage quality rangelands. Figure 4 also suggests that on average, the BG and PV shares are slowly increasing while the NPV share slowly declines. These trends suggests some ambiguity as to whether rangeland quality is improving or declining on average over time.

Figures 5 and 6 provide visual comparisons of trends in RH indicators conditional on exposure to IBLI. Figure 5 compares exposed and unexposed HUC-12 units at the extensive margin (i.e., a unit is exposed once ≥ 1 TLU is insured) using IDW exposure. Figure 6 compares exposed and unexposed HUC-12 units at the intensive margin where a unit is considered exposed once ≥ 500 cumulative TLUs are insured, near the mean cumulative exposure of 521 TLUs at the HUC-12 level over 2010-2020. Both figures depict variation in fractional cover share and EVI across all rangeland types. Analogous figures featuring comparisons in conditional trends for all, high, and low groups are provided in Appendix B.3. The associated trends are very similar across groupings.[18]

[18] Respective figures in Appendix B.3 showcase differences at higher levels of intensive margin exposure at the HUC-12 level as well as extensive and intensive margin figures at the larger HUC-8 level, including variation across all, low, and high groupings.

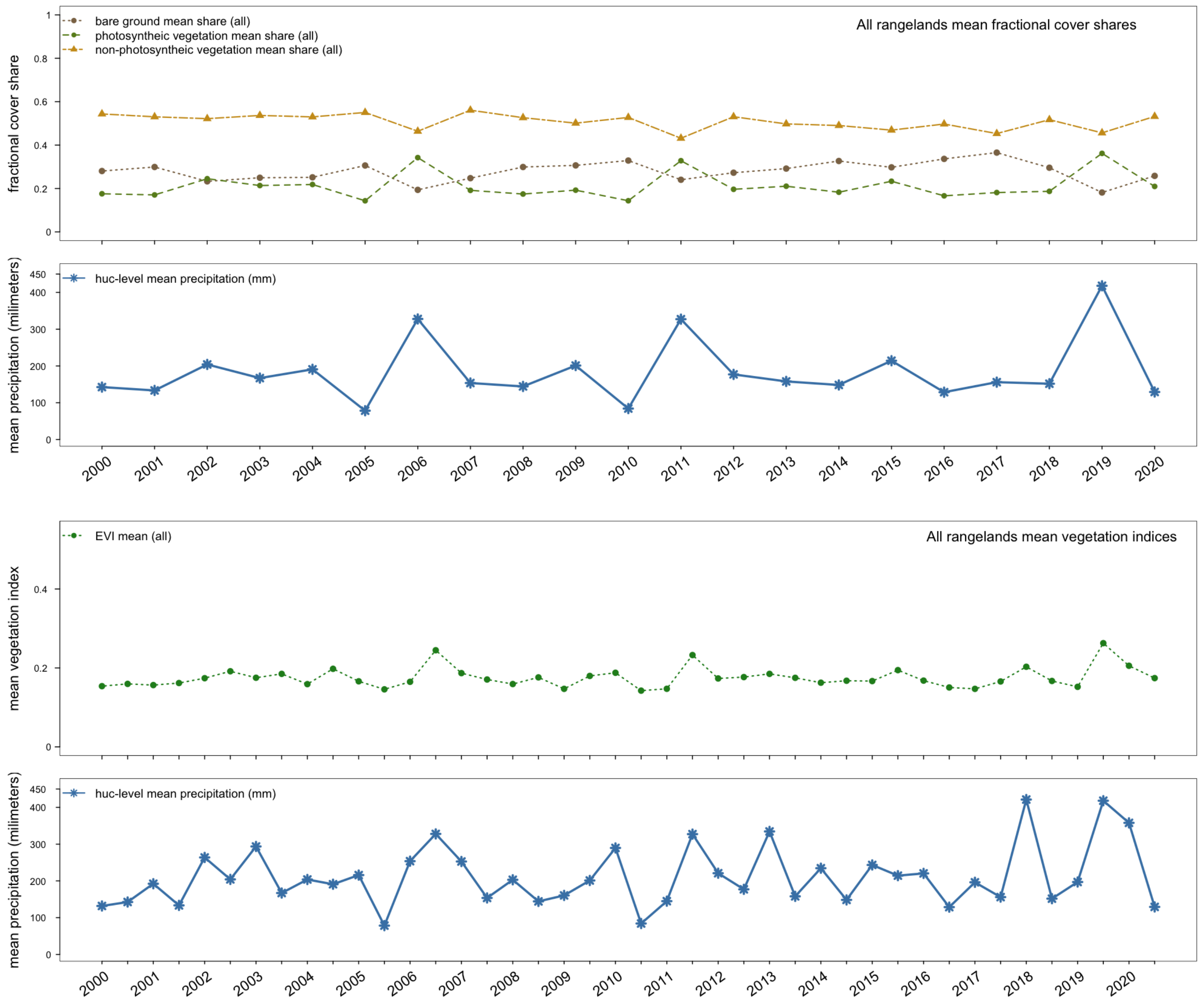

Figure 4: Trends at the HUC-12 level for mean fractional cover shares for all rangelands in the SRSD (top), mean precipitation in the SRSD (second from top), mean EVI in the SRSD and LRLD for all rangelands (third from top), and contemporaneous seasonal average precipitation (bottom panel).

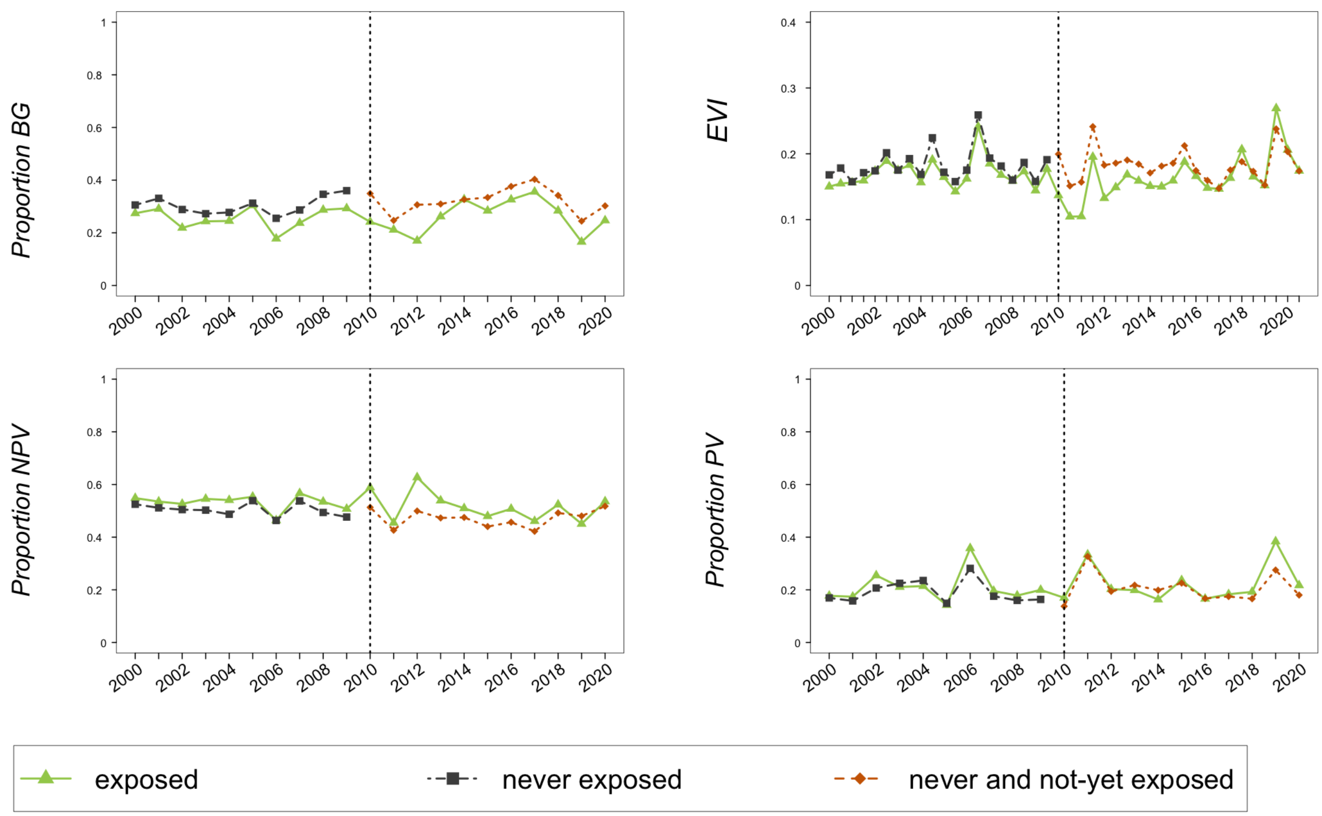

Figure 5: Extensive margin conditional trends in rangeland health measures across all rangeland types at the hydrologic unit 12 level (HUC-12); exposure defined as having ≥ 1 TLU insured. Top row: average proportion of bare ground (BG); average enhanced vegetation index (EVI). Bottom row: average proportion of non-photosynthetic vegetation (NPV); average proportion of photosynthetic vegetation (PV). Vertical dashed lines indicate when IBLI launched in 2010.

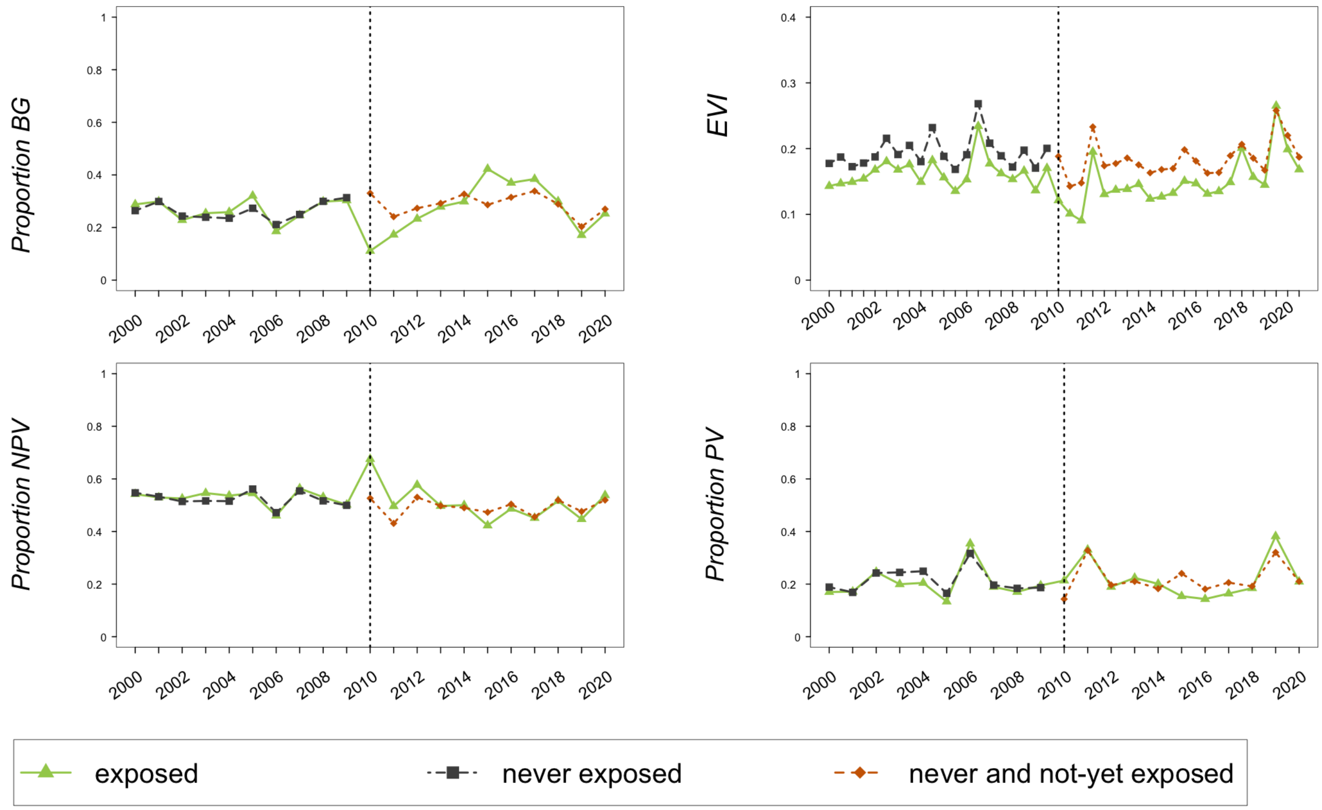

Figure 6: Intensive margin conditional trends in rangeland health measures across all rangeland types at the hydrologic unit 12 level (HUC-12); exposure defined as $\geq$ 500 cumulative TLUs insured. Top row: average proportion of bare ground (BG); average enhanced vegetation index (EVI). Bottom row: average proportion of non-photosynthetic vegetation (NPV); average proportion of photosynthetic vegetation (PV). Vertical dashed lines indicate when the first units were exposed to $\geq$ 500 TLUs insured in 2010.

While these figures do not offer formal tests of either parallel trends pre-IBLI between exposed and unexposed units nor of the impacts of IBLI on these indicators, Figures 5 and 6 show that exposed and never exposed averages followed very similar time paths prior to the 2010 launch of IBLI. In a few indicators and years, observable differences seem to appear following exposure to IBLI, which are somewhat more apparent at the intensive margin (Figure 6). Figures 5 and 6 do not provide strong suggestive evidence of any large IBLI impact on rangelands. They are more consistent with the null hypothesis of neutral effects of IBLI on RH. The lack of any discernible aggregate conditional trends suggests that the fixed effect terms in the econometric estimation are not hiding some salient trend.

4 Econometric Methods

The central question we seek to answer is whether the introduction and scaling of the microfinance product IBLI had unintended effects on the rangelands that support pastoralism. Although we will ultimately use more sophisticated staggered DiD estimators, we illustrate the problem initially with a standard two-way fixed effects (TWFE) specification:

$$Y_{i,r,s,t} = D_{ist}\delta + \mathbf{X'_{i,s,t}}\alpha + \gamma_i + \sigma_t + \nu_{i,r,s,t} \tag{2}$$

where δ captures the average effect of the IBLI exposure dummy variable D_{ist} for areal unit i in rangeland type r in season s and IBLI-year t on RH indicator Y.[19] The vector $\mathbf{X}'$ includes measures of average precipitation or precipitation variability and binned hours of temperature exposure, and γ_i and σ_t represent unit and time fixed effects, respectively. Our construction of D_{ist} assumes regular movement of herders across rangeland types such that once a spatial unit is exposed to IBLI, all rangeland types within that unit are exposed. Construction of D_{ist} also assumes herders' movements across unit boundaries as modeled using IDW (Section 2.3). Since weather processes are more smooth over space than rangeland type variation r we rely on weather realizations summarized across the entirety of each unit i in periods s and t.

We implement two sets of tests for the appropriateness of TWFE for DiD estimation suggested by Jakiela (2021). First, we residualize D_{ist} by regressing it on time and location fixed effects. We then study the distributions of residualized D_{ist} by exposed and comparison (not-yet or never exposed) groups, to check for negative weights among the exposed group. Second, we employ optimal binscatter methods from Cattaneo et al. (2024) to semiparametrically regress residualized outcomes Y against residualized D and apply formal tests of the null hypothesis for treatment effect heterogeneity, which implies a linear relationship between residualized Y and D. As we report in Section 5.1, these tests confirm that TWFE

[19] An 'IBLI-year' begins March 1. Thus our year 2010 reflects the first year of IBLI exposure, from March 1, 2010, through February 28, 2011.

estimation would be inappropriate for these data.

We therefore rely on the two-stage approach developed by Gardner et al. (2025), which (unlike other staggered DiD estimators) accommodates time-varying covariates. At a sub-annual level, controlling for local seasonal weather variation is especially essential, not least of which because the widespread impression in this region is that droughts have occurred with increasing frequency and intensity since 2000 (Haile et al. 2020). Recent work on rangelands also demonstrates the critical nature of weather variation in driving changes in rangeland conditions (Purevjav et al. 2025). If the background weather process has been evolving with climate change during the post-exposure period, failure to control for it may bias our estimates of the impact of IBLI on rangelands.

Gardner et al. (2025) introduce a two stage estimator in which the first stage regresses Y on all covariates and fixed effects using only untreated observations in order to residualize outcomes Y. In the second stage, the estimator regresses residualized Y from all observations on a treatment dummy or event-time dummies to obtain overall and event-time average treatment effects on the treated (ATT) respectively, following the steps outlined below.

Step 1: For a given binary measure of treatment D_{ist} (e.g., extensive or intensive margin indicator), subset to the unbalanced panel of never and not-yet-exposed observations (i.e., such that $D_{ist} = 0$) and regress $Y_{i,r,s,t}$ on fixed effects and controls $\mathbf{X}_{i,s,t}$:

$$Y_{i,r,s,t} = \mathbf{X}'_{\mathbf{i,s,t}}\theta + \gamma_i + \sigma_t + \mu_{i,r,s,t} \tag{3}$$

Step 2: Take the $\widehat{\theta}$, $\widehat{\gamma}_i$, and $\widehat{\sigma}_t$ estimates from step 1 and regress residualized $Y_{i,r,s,t}$, defined as $\ddot{Y}_{i,r,s,t} \equiv Y_{i,r,s,t} - \mathbf{X}'_{\mathbf{i,s,t}}\widehat{\theta} - \widehat{\gamma}_i - \widehat{\sigma}_t$, on treatment dummy D_{ist}:

$$\ddot{Y}_{i,r,s,t} = D_{ist}\beta + \ddot{\varepsilon}_{i,r,s,t} \tag{4}$$

In the second step β reflects the overall ATT across group-time cohorts, a weighted ATT across all potentially heterogeneous treatment effects and exposure cohorts at a given level of exposure. Other ATTs can be computed in similar fashion with dummy variables that reflect any heterogeneity of interest, in our case for high and low quality rangelands. For example, an event study plot reflecting all group-time cohorts can be obtained by replacing D_{ist} with a vector of event-time dummies $\mathbf{W'}_{ist}$ to trace out the dynamic treatment effects in each post-treatment period across all group-time cohorts.

The identifying assumption is that conditional on the time-varying covariates, IBLI exposure is orthogonal to any time-and-spatially-varying heterogeneity that is correlated with rangeland conditions. All DiD estimation relies on satisfaction of a credible version of the parallel trends assumption for causal identification. In the staggered DiD setting, comparatively strong and weak versions of the parallel trends assumption exist, depending on the estimator. Gardner et al. (2025) rely on estimation of pre-treatment leads on the residualized outcome from the first stage. Coefficients for dummies estimated for pre-treatment leads within $\mathbf{W'}_{ist}$ provide suitable placebo tests for the plausibility of parallel trends (i.e., the null hypothesis that respective coefficients equal zero). Respective coefficients have the interpretation of measuring average deviations from never-treated trends.

There are two primary challenges to our causal identification strategy. First, for all of our remotely sensed variables – both our weather controls and our RH outcome variables – there exists a possibility of nonrandom prediction error that could bias estimates (Jain 2020). Garcia and Heilmayr (2024) and Alix-García and Millimet (2023) develop methods to mitigate these kinds of issues when outcome variables are binary. Since we use aggregated variables at an areal unit level as discussed in Section 2.3 these alternatives do not apply. As such, we note that our estimates are conditional on the maintained assumption of non-classical-error-free remote sensing measures. Classical measurement error should not bias our estimates, since there is no measurement error in the main explanatory variable of interest, exposure to IBLI. Second, if the parallel trends assumption is not satisfied, our estimated ATTs may be biased. We therefore implement Rambachan and Roth (2023)'s robustness checks that account for various violations of parallel trends. Our implementation utilizes software from Butts and Gardner (2021).

5 Differences-in-Differences Estimation Results

5.1 Two-Way Fixed Effects & Diagnostics

Jakiela (2021)'s tests confirm that TWFE is inappropriate for causal identification with our data, yielding negative weights among earlier treated units in later periods, and rejecting the null hypothesis of treatment effect homogeneity.[20] In addition, semi-parametric optimal binscatter tests (Cattaneo et al. 2024) reject the linearity assumption (see Figures C.3 - C.5) as well as the null hypothesis that the response function between residualized outcomes and residualized treatment dummy is the same between exposed and unexposed units (Table C.2). Hence our reliance on more robust methods.

5.2 Staggered DiD Estimates: Extensive Margin Tests

Figure 7 presents results for all rangelands with 95% confidence intervals estimated using Gardner et al. (2025)'s two-stage DiD estimator, where the treatment dummy of interest captures IBLI exposure at the extensive margin based on IDW exposure at the HUC-12 level. We cannot reject the null hypothesis of no effects on any fractional land cover measure. Not only are all estimated treatment effects for BG, NPV and PV statistically insignificantly different from zero, but the magnitude of each point estimate is no more than one percent in absolute magnitude. These are rather precisely estimated zero effects. We do, however, reject the no effects null for EVI. Specifically, we find a positive effect of IBLI exposure on EVI of around 0.006, which is statistically significant at the 1% level. This is consistent with previous empirical findings that IBLI reduced precautionary savings in kind, i.e., in the form of livestock (Jensen, Barrett, and Mude 2017; Barrett et al. 2025). Additional estimates in Appendix D.1 provide qualitatively similar estimates at the extensive margin and show comparisons of effects across all, low, and high rangeland subsets. Respective figures show

[20] Appendix C reports TWFE estimation results from equation (2) (Table C.1) and the distribution of weights between exposed and comparison units over time (Figures C.1 and C.2).

extensive margin results with and without inverse distance weighting (Figure D.1.1 versus D.1.2), as well as results at the HUC-9, HUC-8, and IU levels (Figures D.1.3 - D.1.5).

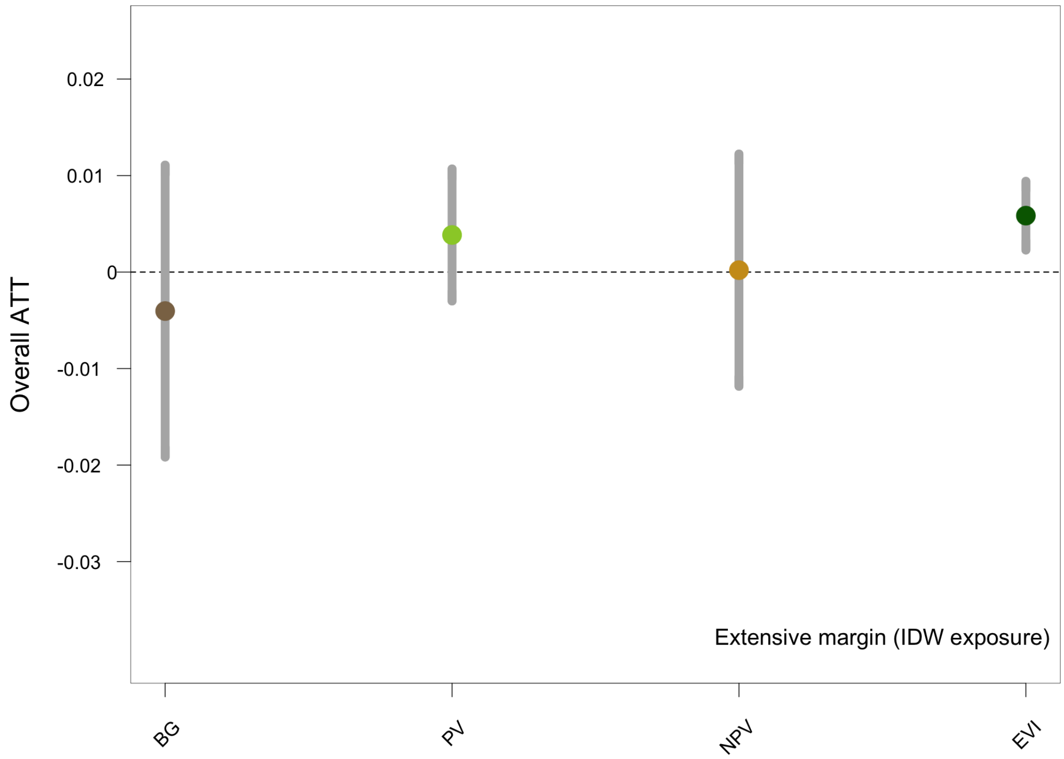

Figure 7: Overall ATTs with 95% confidence intervals for tests of impacts at HUC-12 level from IBLI exposure at the extensive margin based on the sum of IDW exposure ($\geq$ 1 TLU insured). ATTs reflect point estimates of β in equation (4). Standard errors are clustered at the index unit level. From left to right, estimated coefficients reflect IBLI's impacts on BG, PV, NPV and EVI within all rangelands (see Section 3). The number of observations for respective estimations are: fractional cover all mask, $n = 99,468$; EVI all mask, $n = 199,500$. First stage covariates are the same across models and include: the mean and standard deviation of seasonal precipitation (mm), and mean GDD in 5° C bins with the exception of two 10° C bins from 5-10° C and 30-45° C due to limited exposure from 5-10° C and 35-40° C. Each model includes unit and period fixed effects.

The unbiasedness of these estimates depends on satisfying the parallel trends assumption during the pre-exposure period. Figure 8 presents event study plots for BG, PV, and EVI within all rangelands that trace the dynamic treament effects across all group-time cohorts and estimated coefficients sufficient for a test of the presence of pre-trends.

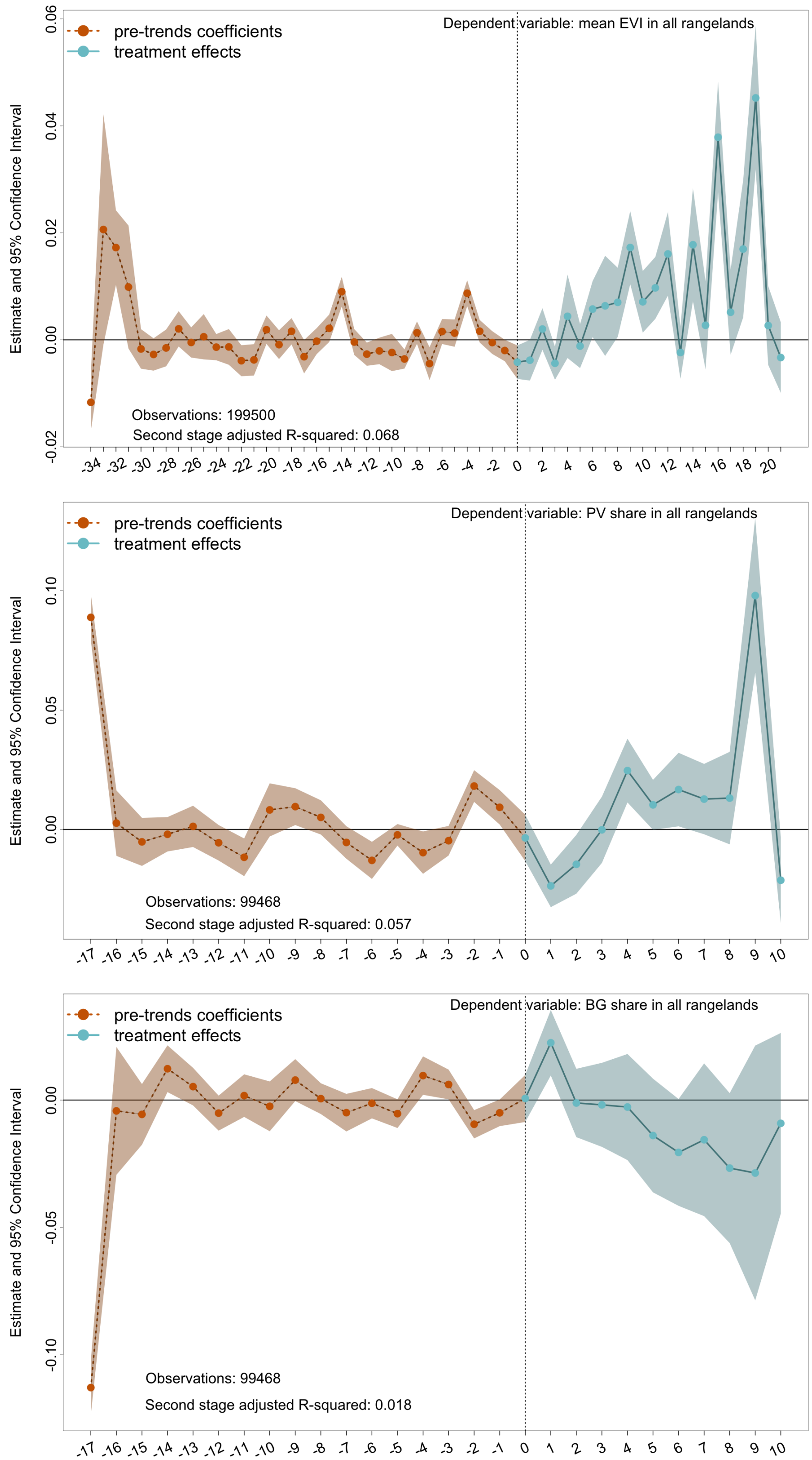

Figure 8: Event studies for the effect of IBLI at the extensive margin ($\geq$ 1 TLU insured) on EVI, PV, and BG within all rangelands using inverse distance weighting (IDW) (see Section 2.3). Standard errors are clustered at the index unit level.

Although most pre-exposure coefficient estimates are statistically insignificantly different from zero (Figure 8), several are statistically different from zero. Thus estimated treatment effects at the extensive margin may be biased. However, the dynamics apparent in these event study plots may reflect, in part, natural variation in RH measures, which fluctuate in conjunction with time-varying unobserved factors (e.g., wildlife grazing pressures, lightning strikes, or human initiated fire) unrelated to IBLI rollout.

These results are consistent with IBLI having a neutral to positive impact on rangelands. However, since pre-exposure parallel trends tests do not uniformly support the parallel trends assumption at the extensive margin, these estimates may be biased. A more realistic test of IBLI's impacts on rangelands will account for variation at the intensive margin of IBLI exposure, to which we now turn attention.

5.3 Staggered DiD Estimates: Intensive Margin Tests

We implement tests of IBLI's effect at the intensive margin using two complementary approaches supported by Gardner et al. (2025): binned and continuous. Table 1 presents results at the HUC-12 level based on a continuous measure of exposure, defined as the cumulative sum of IDW exposure defined, across all rangelands. Figure 9 presents results for binned intensive margin exposure defined as exposure to ≥ 500 cumulative TLUs insured, which is very to close the 2010-2020 mean exposure level of 521.33 TLUs, across all rangelands. Figure 10 provides the corresponding event studies for BG, PV, and EVI for all rangelands. All estimates include unit fixed effects and period fixed effects. All standard errors are clustered at the index unit level.

Both the binned and continuous approaches tell the same story, apparent in comparing column 3 in Table 1 and the overall ATTs captured in Figure 9. As with the extensive margin results, there remains no evidence against the null of no effect on the proportion of land in BG or NPV. However, in addition to evidence for a statistically significant positive effect for EVI, there are now statistically significant, positive effects for PV at the 1% level, which is consistent with the increased greenness finding per the EVI measure. The binned exposure estimates also scale in a consistent manner with the continuous estimates. For example, the ATT for the effect on EVI in all rangelands at the $\geq$ 500 cumulative TLUs insured level is 0.012. The mean exposure level among the HUC-12 units that have been exposured to $\geq$ 500 cumulative TLUs insured level is 1785.19 TLUs. The corresponding ATT (0.011) divided by this mean level of exposure (1785.19) is approximately 0.000006, which is very close to the 0.000005 coefficient estimate in column (3) of Table 1.

The event studies captured in Figure 10 suggest stronger evidence for conditional parallel trends as more coefficient estimates are statistically indistinguishable from zero and pre-trend movement between periods is greatly diminished. These findings offer reasonable support for the identifying assumption that conditional parallel trends hold for above-mean intensive margin exposure to IBLI.

These results withstand a variety of robustness checks. First, we implement alternative first stage specifications that include unit-specific linear trends in addition to unit and period fixed effects. Table 1 column 4 shows the results; Appendix D.2 reports the corresponding first stage of the results presented in Table 1. Goodness-of-fit statistics (e.g., RMSE, AIC, BIC, Adjusted R-squared) for the first and second stages are somewhat worse, associated coefficient estimates change sometimes markedly so in terms of sign, magnitude, and significance, and event studies do not appreciably differ from a conditional parallel trends perspective. These findings lead us to favor estimations with seasonal weather controls and unit and period fixed effects, the predictive power of which is stronger (Appendix D.2).

Second, we implement a variety of estimations using the continuous and binned exposure levels at different levels of spatial aggregation which are provided in Appendix D.2. Table D.2.5 shows analogous output to Table 1 at the HUC-9 level and the results are very similar. Figures D.2.1-D.2.4 estimate the overall ATTs in analogous fashion to Figure 9 and show the corresponding results across all, low, and high rangeland types for HUC-12, HUC-9, HUC-8, and index unit levels respectively. While HUC-9 and HUC-8 level results are comparable to the HUC-12 level, all effects become null at the IU level. This seems a potential indication of the aggregation bias that can result at a larger areal unit level.

Third, we study the binned exposure approach at increasing levels of intensive margin exposure at the HUC-12 level across all, low, and high rangeland types. In Appendix D.2, overall ATTs are provided in Figures D.2.5-D.2.7 for the intensive margin effect at ≥ 1000, 2000, and 3000 cumulative TLUs insured. Results at the ≥ 1000 cumulative TLUs insured level are comparable to those in Figure 9. At the ≥ 2000 cumulative TLUs insured level, EVI is no longer statistically significant, results for increased PV are larger in magnitude and still significant, and there are statistically significant results for decreased bare ground. This pattern generally remains at the ≥ 3000 cumulative TLUs insured level, though statistically significant reduced bare ground only remains for high forage quality rangelands. A limitation that emerges with increasing levels of binned exposure in this regard is that respective group-time cohorts are observed for increasingly fewer periods, therefore limited observations at these increasing levels of exposure are available. However, since results at the fully continuous margin of exposure are consistent with these general findings and do not support an effect on the proportion of bare ground, this should continue to allay concerns about the consistency of these findings.

Finally, we also apply the 'honest DiD' methods from Rambachan and Roth (2023). In Appendix D.2, Figures D.2.8-D.2.11 show the corresponding results for each post-treatment ATT for BG, PV, and EVI in all rangelands. Since EVI has semi-annual observations the corresponding full set of post-treatment data spans figures D.2.10 and D.2.11. These figures show results for robust 95% confidence intervals for each post-treatment ATT using the "relative magnitude" approach from Rambachan and Roth (2023). This approach uses the maximum observed deviation M from parallel trends in the pre-treatment period to bound potential post-treatment deviations from parallel trends and thereby produce confidence intervals that account for the potential bias. Each figure features the estimated original confidence interval followed by a set of alternative confidence intervals that incorporate an increasing share of the fully value of the observed M. In these figures although we find that our statistically significant results do eventually become statistically insignificant with increasing deviations from parallel trends in the post-treatment period, the overall finding of a broadly neutral to positive effect of IBLI on rangelands remains. The results are also intuitive based on the strength of the results discussed so far. In particular, our results for EVI withstand larger deviations from parallel trends than do our results for fractional cover measures.

The general pattern of impacts at the intensive margin on a continuous basis and above-mean IBLI exposure is consistent with, perhaps even somewhat clearer than the prior extensive margin results. IBLI has neutral to positive impacts on rangelands. The estimates at the intensive margin more strongly support the hypothesis that IBLI may modestly positive effects, particularly for increasing the prevalence of photosynthetic vegetation and the biological productivity of the rangelands. These effects also do not differ by broad quality differences (i.e., high vs. lower forage quality rangelands).

By no means do these results suggest IBLI generated a strong, broad-based improvement in RH. But they do contravene widespread fears – and model-based simulations (John et al. 2019; Bulte and Haagsma 2021) – predicting that IBLI would cause rangeland degradation. The fact that the intensive margin estimates are stronger, and more positive, than the extensive margin effects is especially comforting in that if the ordering were the opposite, one might reasonably worry that continued scaling of IBLI might bring about adverse, but not yet realized effects. These findings are consistent with the prevailing effects coming from reduced precautionary savings in livestock and smaller grazing ranges (Jensen, Barrett, and Mude 2017; Toth et al. 2020; Barrett et al. 2025), which may have allowed rangelands to respond favorably to reduced grazing pressure.

Table 1: Intensive margin tests (overall ATTs) for the effect of IBLI on rangelands using inverse distance weighted (IDW) continuous measures of the total cumulative TLUs insured at the HUC-12 level (see Gardner et al. (2025) pg. 17-18).

	Dependent variable: Bare ground (BG) share all rangelands			
Total cumulative TLUs insured (IDW)	0.000010**	-0.000006***	-0.000004	0.000003
	(0.000004)	(0.000002)	(0.000005)	(0.000003)
BG second stage statistics				
Observations	99,468	99,468	99,468	99,468
Adjusted R^2	0.001	0.005	0.002	0.001
	Dependent variable: Photosynthetic vegetation (PV) share all rangelands			
Total cumulative TLUs insured (IDW)	-0.000005**	0.000009***	0.000009***	-0.000003
	(0.000002)	(0.000001)	(0.000002)	(0.000004)
PV second stage statistics				
Observations	99,468	99,468	99,468	99,468
Adjusted R^2	0.002	0.015	0.014	0.002
	Dependent variable: Non-photosynthetic vegetation (NPV) share all rangelands			
Total cumulative TLUs insured (IDW)	-0.000006*	-0.000003*	-0.000005	0.0000009
	(0.000004)	(0.000002)	(0.000004)	(0.000004)
NPV second stage statistics				
Observations	99,468	99,468	99,468	99,468
Adjusted R^2	0.0007	0.001	0.004	0.00010
	Dependent variable: Enhanced vegetation index (EVI) all rangelands			
Total cumulative TLUs insured (IDW)	-0.0000009	0.000002***	0.000005***	0.000003**
	(0.000001)	(0.0000005)	(0.000001)	(0.000001)
EVI second stage statistics				
Observations	199,500	199,500	199,500	199,500
Adjusted R^2	0.0001	0.004	0.024	0.010
First stage specifications (BG, PV, NPV, EVI)				
Unit fixed effects	No	Yes	Yes	Yes
Period fixed effects	No	No	Yes	Yes
Unit-specific trends	No	No	No	Yes

Note: First stage covariates are the same across models and include: the mean and standard deviation of seasonal precipitation (mm), and mean GDD in 5° C bins with the exception of two 10° C bins from 5-10° C and 30-45° C due to limited exposure from 5-10° C and 35-40° C. Standard errors are clustered at the level of index unit level. *p<0.1; **p<0.05; ***p<0.01.

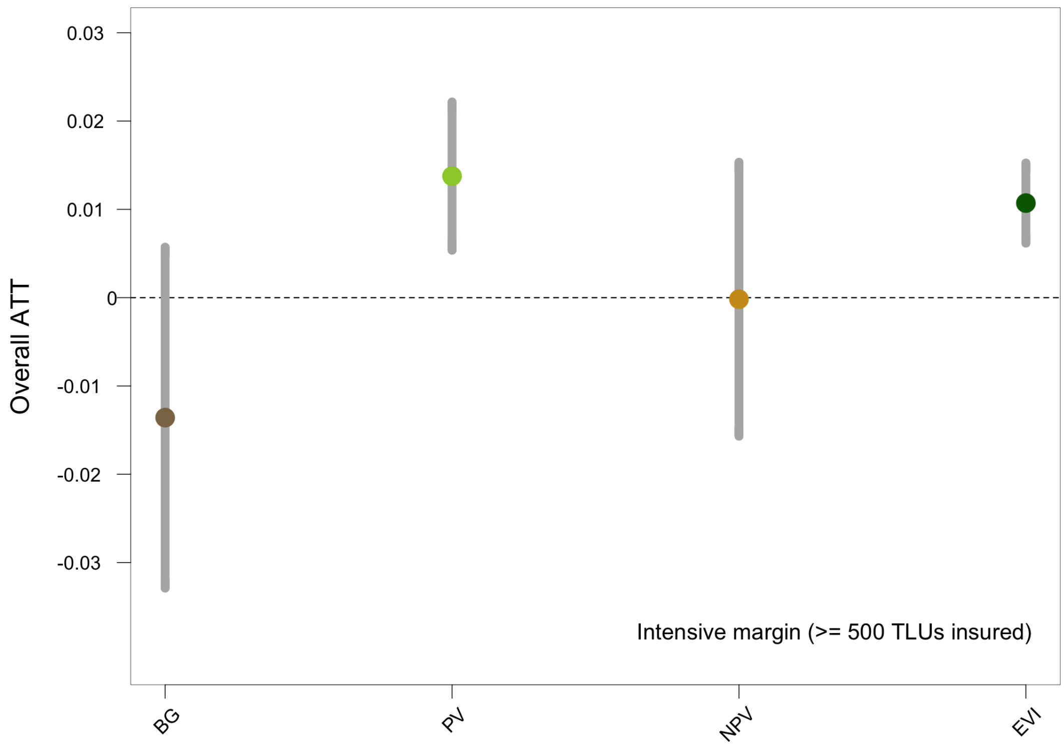

Figure 9: Overall ATTs with 95% confidence intervals for tests of impacts at HUC-12 level from IBLI exposure at the intensive margin of $\geq$ 500 TLUs insured. ATTs reflect point estimates of β in equation (4) from Gardner et al. (2025). Standard errors are clustered at the index unit level. From left to right, estimated coefficients reflect IBLI's impacts on BG, PV, NPV and EVI within all rangelands (see Section 3). The number of observations for respective estimations are: fractional cover all mask, $n = 99,468$; EVI all mask, $n = 199,500$. First stage covariates are the same across models and include: the mean and standard deviation of seasonal precipitation (mm), and mean GDD in 5° C bins with the exception of two 10° C bins from 5-10° C and 30-45° C due to limited exposure from 5-10° C and 35-40° C. Each model includes unit and period fixed effects.

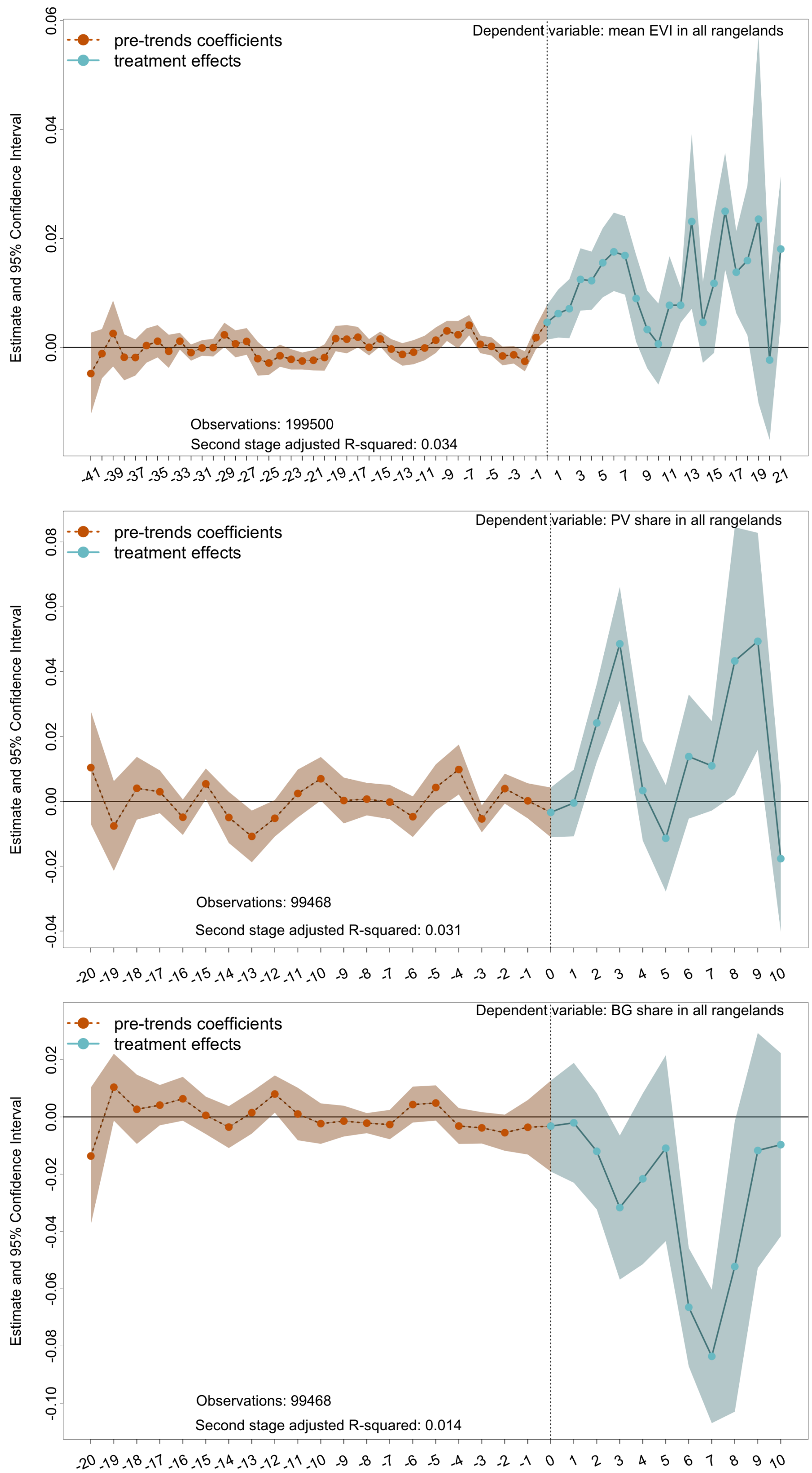

Figure 10: Event studies for the effect of IBLI at the intensive margin (≥ 500 cumulative TLUs insured) on EVI, PV, and BG within all rangelands using inverse distance weighting (IDW) (see Section 2.3). Standard errors are clustered at the index unit level.

6 Conclusions

Microfinance, including agricultural index insurance, has become extremely popular over the past quarter century, to the point that Muhammad Yunus, the founder of Grameen Bank, won the 2006 Nobel Peace Prize. If microfinance stimulates economic activity and investment, however, it could also have unintended environmental consequences, perhaps especially in lands without clear, strong private property rights (Noack and Costello 2024). In case of microinsurance against catastrophic drought losses, the central premise of the product depends on it not causing serious adverse impacts on the natural environment that support human well-being. By rigorously testing for IBLI's impacts on rangelands, we directly confront this key question as the product scales rapidly across East African rangelands.

The question requires empirical investigation because IBLI's potential impacts on rangelands are analytically ambiguous. It could increase or decrease herd sizes and expand or shrink grazing ranges. Empirical work to date yields conflicting findings for the direction of impact on herd sizes (Jensen, Barrett, and Mude 2017, Matsuda, Takahashi, and Ikegami 2019, Barrett et al. 2025) and herding effort (Toth et al. 2020, Son 2025). Now that adequate, high quality data exist on east African rangelands health over an extended period (Soto et al. 2024), which we can merge with administrative data on IBLI exposure, we can directly test what effects, if any, IBLI has had on rangelands.

Using a DiD estimator designed for staggered roll-out while controlling for time-varying controls (Gardner et al. 2025), we find strong evidence against the hypothesis that IBLI has adversely affected east African rangelands. If anything, the evidence points to neutral-to-positive impacts on rangeland quality, at both the extensive margin of initial exposure to IBLI and, especially, at the intensive margin, once locations accumulate sufficient exposure to IBLI for any induced effects to become more observable. We find statistically significant improvements in rangeland biological productivity, as well as an increased share of land covered in photosynthetic vegetation.

These reduced form findings offer reassurance that the worst fears about IBLI have not come to fruition nor is there any support in the data that they are likely to materialize as the product scales further. Our findings after eleven years of IBLI staggered roll-out to nearly 3.2 million herders across a vast area of southern Ethiopia and Kenya disprove the IBLI-induced "tragedy of the commons" hypothesis. Insurance companies, governments, and international donors can continue to promote IBLI comfortable in the knowledge that offering microfinancial protection against catastrophic drought risk is not degrading the rangelands on which pastoralists' livelihoods depend.

A natural extension to this work would explore the structural foundations of this empirical result. What combination of returns to livestock keeping, pastoralist risk preferences and grazing behaviors, along with product characteristics – specifically, loss reduction based on the strike level and basis risk – plausibly result in induced reductions in precautionary savings in kind that neutralize, perhaps even dominate insurance's investment inducing effects? That sort of structural exploration can inform a broader understanding of the conditions under which our empirical findings might be generalizable, that is, when microfinance expansion can be reasonably expected not to adversely impact the natural environment across a range of contexts.

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