The Environmental Impacts of Scaling a Microfinancial Product: Index-Based Livestock Insurance and East African Rangelands

Steven W. Wilcox, Christopher B. Barrett, Nathaniel Jensen, Patrick E. Clark, Francesco Pietro Fava, Gerardo E. Soto, Njoki Kahiu, Ying Sun*

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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 East Africa 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. 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 condition measures 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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*Wilcox: Department of Applied Economics, Utah State University (USU), and USU Ecology Center, Logan, UT 84322, USA, steven.wilcox@usu.edu. Barrett: Charles H. Dyson School of Applied Economics and Management, Jeb E. Brooks School of Public Policy, and Cornell Atkinson Center for Sustainability, Cornell University, Ithaca, NY 14853, USA, cbb2@cornell.edu. Jensen: University of Edinburgh, Edinburgh, UK, EH8 9YL, njensen@ed.ac.uk. Clark: USDA-Agricultural Research Service, Boise, ID 83702, USA pat.clark@usda.gov. Fava: Department of Environmental Science and Policy (ESP), Università degli Studi di Milano, Via Celoria 2, 20133 Milan, Italy, fava@unimi.it. Soto: Instituto de Estadística, Universidad Austral de Chile, Chile, gerardo.soto@uach.cl. Kahiu: Department of Plant and Environmental Sciences, New Mexico State University, NM, USA, nkahiu@nmsu.edu. Sun: School of Integrative Plant Science, Soil and Crop Sciences Section, Cornell University, Ithaca, NY 14853, USA, ys776@cornell.edu. We gratefully acknowledge financial support from the CGIAR Standing Panel on Impact Assessment, data support from the International Livestock Research Institute, excellent research assistance from Shilvaan Patel, and contributions from Benjamin Porter, and Chuan Liao. We are grateful for helpful comments received from Kathy Baylis, Joel Ferguson, John Gardner, David Just, C.-Y. Cynthia Lin Lawell, Ariel Ortiz-Bobea, Liz Tennant, several anonymous reviewers, and seminar participants at AAEA, Cornell, ICAE, NC-1034, SPIA, Texas A&M, WAEA, and CEAR. All errors are our own.

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 and weather the shocks that buffet them (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 et al. 2012 and Cull and Morduch 2018). Index insurance against crop and livestock loss is one promising element of the broader microfinance movement (Carter et al. 2017).

Far less attention has been paid to whether improved access to financial products, including insurance, might generate unintended negative impacts on the natural systems that disproportionately support the livelihoods of the rural poor. By increasing the risk-adjusted returns, 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, per the Borlaug hypothesis (Stevenson et al. 2013; Villoria 2019a,b), supporting transitions out of natural resource extraction industries, or reducing risk management behaviors that degrade nature (Barrett 1999; Gollin et al. 2021; Wilcox et al. 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 credit markets in the context of fisheries and forests, we know of no evidence with respect to rangelands, the dominant land type on Earth, nor on microinsurance or other traditional micro-financial products.

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 et al. 2017; Janzen and Carter 2019; Tafere et al. 2019; Janzen and Carter 2019; Stoeffler et al. 2022; Barrett et al. 2025; Gehring and Schaudt 2024; Jensen et al. 2025; Sakketa et al. 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. 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. These possibilities mimic the Jevons Paradox of agricultural productivity growth, wherein higher returns induce extensification into previously uncultivated lands. Conversely, 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 et al. 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 et al. 2025). Or insurance access might induce investments in boosting livestock productivity with less intensive rangelands use, per the Borlaug hypothesis (Jensen et al. 2017). The net environmental impacts of index insurance are therefore analytically ambiguous and an open empirical question.[1] A vibrant literature on agricultural development and land use has explored the tension between the Borlaug hypothesis and Jevons Paradox relating crop agriculture to deforestation (Stevenson et al. 2013; Villoria 2019a; Pelletier et al. 2020; Jayachandran 2022; Balboni et al. 2023), but there has been little work on analogous issues concerning livestock husbandry and rangelands.

This paper examines the environmental impacts of long-term access to index insurance at scale. It does so by exploiting a new, high spatial resolution data set from 2000-2020

[1] Bhattacharya and Osgood (2014) develop an analytical model to study the impact of weather index insurance on the commons in low income settings and demonstrate the ambiguity of the direction of environmental impacts. Prior empirical research on agricultural insurance and environmental impacts includes Walters et al. (2012) and Smith and Goodwin (2013) on the impacts of crop insurance programs in the United States, and Feng et al. (2021) on reductions in pesticide use in China. Empirical work on credit access has shown beneficial impacts in global fisheries conditional on secure property rights (Noack and Costello 2024), and in reducing deforestation in Brazil conditional on land titling and environmental regulation compliance (Assunção et al. 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) (Soto et al. 2024). 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 (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 for the environmental impact of a microfinancial product.

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 et al. 2017, Janzen and Carter 2019, Tafere et al. 2019; Barrett et al. 2025; Gehring and Schaudt 2024; Jensen et al. 2025; Sakketa et al. 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 have predicted that IBLI and rangeland-oriented index insurance might have negative impacts on rangelands, though these studies have relied on strong, untested assumptions (Müller et al. 2011; John et al. 2019; Bulte and Haagsma 2021). Empirical findings suggest that IBLI has 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 a 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. 2018b).

Across a series of rangeland health indicators (described in Section 3.3), we find no evidence of negative rangeland quality impacts from IBLI. On the contrary, IBLI's environmental impacts range from neutral to statistically significantly positive. At the extensive margin, we find mostly precisely-estimated null results with the exception of small but statistically significant increases in rangeland biological productivity indicators (e.g., reflectance-based 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 generally precise null effects on both bare ground and non-photosynthetic vegetation cover. These findings are encouraging and allay concerns regarding IBLI's potential to induce negative impacts on rangeland systems.

2 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 et al. 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, leading Garrett Hardin to famously reference extensive livestock grazing to motivate his 'tragedy of the commons' hypothesis.[4] Pastoralists in the region have historically used mobility to manage drought risk exposure by adjusting seasonal and daily movements in response

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

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

[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."

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 region's bimodal rainfall patterns, 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 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 insurance underwriters' operational capacity, their retail sales agents, and regulators (Johnson et al. 2019; Jensen et al. 2024). This generates plausible exogeneity in the timing of rangelands IBLI exposure at the extensive margin, enabling evaluation of microinsurance's impacts on rangelands. Exposure at the intensive margin, however, was potentially endogenous to rangeland conditions that affect pastoralists' demand for IBLI (Jensen et al. 2018). We discuss in Section 4 how we deal with that prospective endogeneity.

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

To enhance our study area, 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 product design, and staffing, IBLI was not offered in those regions by 2020. IBLI is now expanding into these 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.

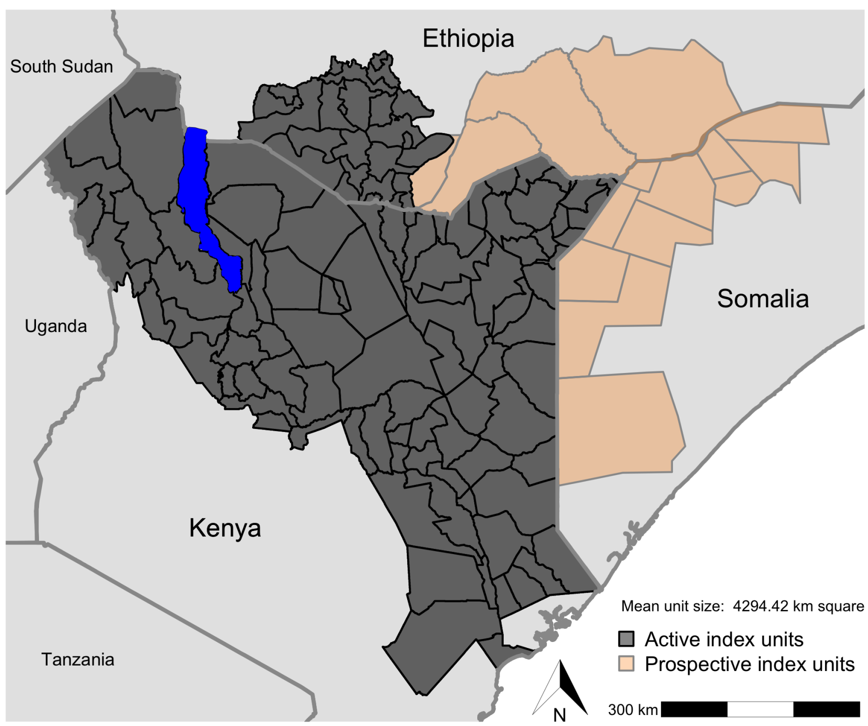

Figure 1: Active IUs span the northern and eastern portions of Kenya and part of southern Ethiopia, and are shaded in dark grey. Prospective IUs in which IBLI was not yet introduced during our study period in southern Ethiopia and western Somalia provide plausible control units and are shaded orange.

3 Data

3.1 IBLI administrative data and 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 total TLUs insured by year and season, as well as private IBLI 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 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.1 provides analogous two-way plots, which feature additional measures of rangeland area exposed by low and high forage quality rangeland types (Figure A.1.1), measures of the total number of policies (Figure A.1.2), cumulative TLUs, policies, and exposed rangeland area (Figure A.1.3), and an animation of contemporaneous IBLI coverage over space and time at the IU level (Figure A.1.4).

[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.

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

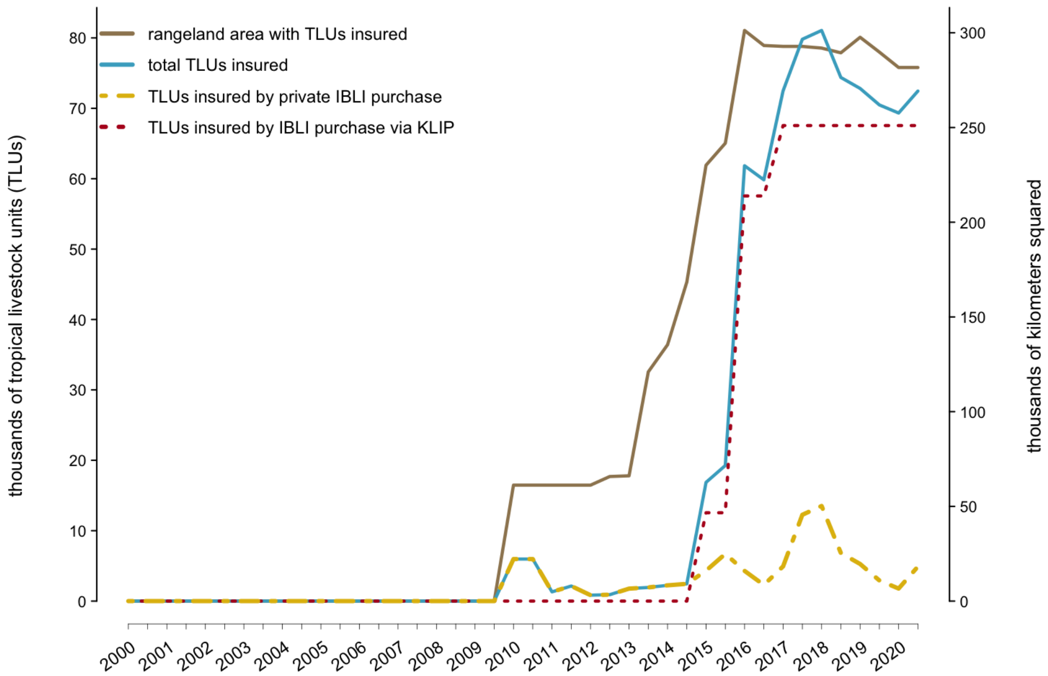

Figure 2: IBLI expansion in thousands of TLUs insured and area of rangelands exposed in thousands km^2.

3.2 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 conditions and quality (on this see more in Section 3.3) 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 et al. 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 scale issues, we study four different levels of spatial aggregation. This approach 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 et al. 2016). At the largest aggregate level we use IUs (Figure 1), and we also study sub-watershed unit levels 8, 9, and 12, also known as hydrologic unit code boundaries

(HUCs, hereafter) from Lehner and Grill (2013). Watersheds have geophysical boundaries set by the biophysical processes (e.g., hydrology, geology, topography) that drive underlying rangeland ecosystems and grazing patterns, thereby offering natural spatial units of analysis for this study. The number of unique units that intersect our study area within each level of aggregation and their average size in terms of area are: 130 and 4,294 km^2 (IUs); 870 and 739 km^2 (HUC-8); 2339 and 263 km^2 (HUC-9); 4753 and 125 km^2 (HUC-12). Figure 3 depicts our HUC-12 units (Appendix Figures A.1.5 - A.1.6 show respective maps for HUC-8 and HUC-9). Final panels are nearly perfectly balanced at each watershed unit level; slight panel imbalance occurs for several innocuous reasons (see further details in Section 5).

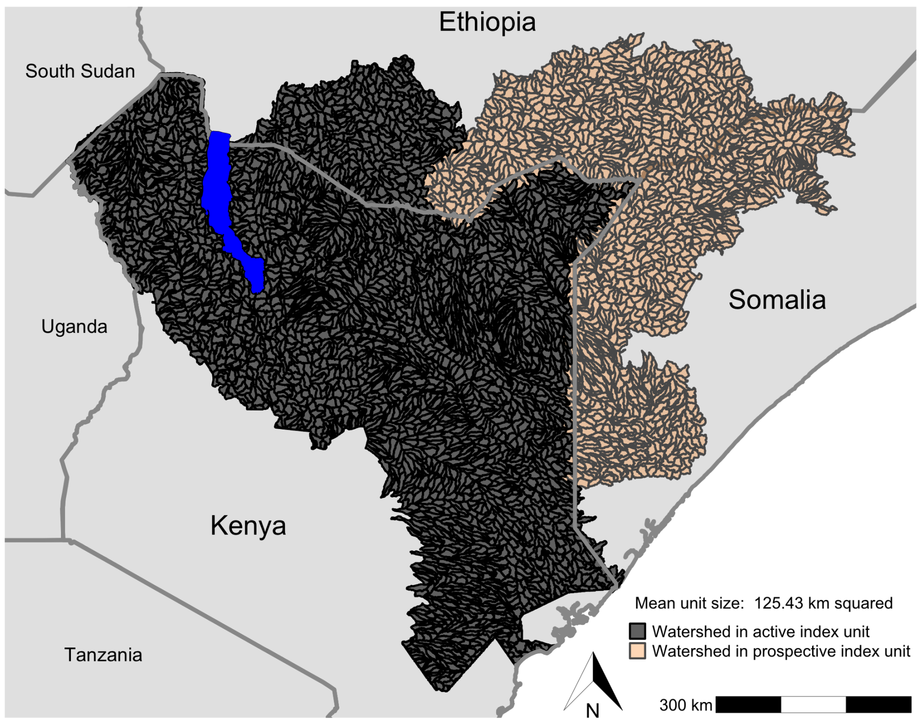

Figure 3: Map of study area and intersecting HUC-12 units from Lehner and Grill (2013).

To account for potential spillover effects from herders grazing across unit boundaries, we apply an inverse distance weighting (IDW)[8] algorithm, 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, 2018a). 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

[8]IDW amounts to an application of a gravity model (Carrère et al. 2020) and has been used in spatial statistics and other econometric studies of rangelands (Purevjav et al. 2025).

SRSD season over 2011-2015. This is a conservative distance as herding distances tend to be a bit larger in the SRSD. Respective equations and algorithms to implement IDW in our setting are detailed in Appendix A.2. Appendix Figure A.2.1 shows boxplots of seasonal livestock herding distance distributions and Appendix Figure A.2.2 shows example neighborhood buffers for a watershed unit near Lake Turkana.

To study IBLI exposure we focus on cumulative TLUs insured at the extensive and 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 ≥ 1 cumulative TLU is insured within a unit as measured by our IDW approach. 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 4 provides counts of the number of exposed versus unexposed units over time at the HUC-12 level and provides contrasting counts with and without IDW. The top panel of Figure 4 contrasts measures of extensive margin IBLI exposure at the HUC-12 level, with and without IDW. Notably, the number of exposed units increases with IDW. The bottom panel shows the distribution of treated versus control units at increasing levels of intensive margin exposure using IDW (e.g., ≥ 500 cumulative TLUs insured). 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 A.2 provides a variety of additional supporting information, including: spatial animations at the HUC-12 level showing how our IDW approach impacts contemporaneous and cumulative IBLI exposure (Figures A.2.3-A.2.4); the cumulative distribution function of cumulative IDW exposure (Figure A.2.5); and a table of summary statistics on IBLI exposure (Table A.2.1) over 2010-2020 for each level of aggregation and by differing approaches to measuring exposure (e.g., contemporaneous without IDW versus cumulative with IDW).

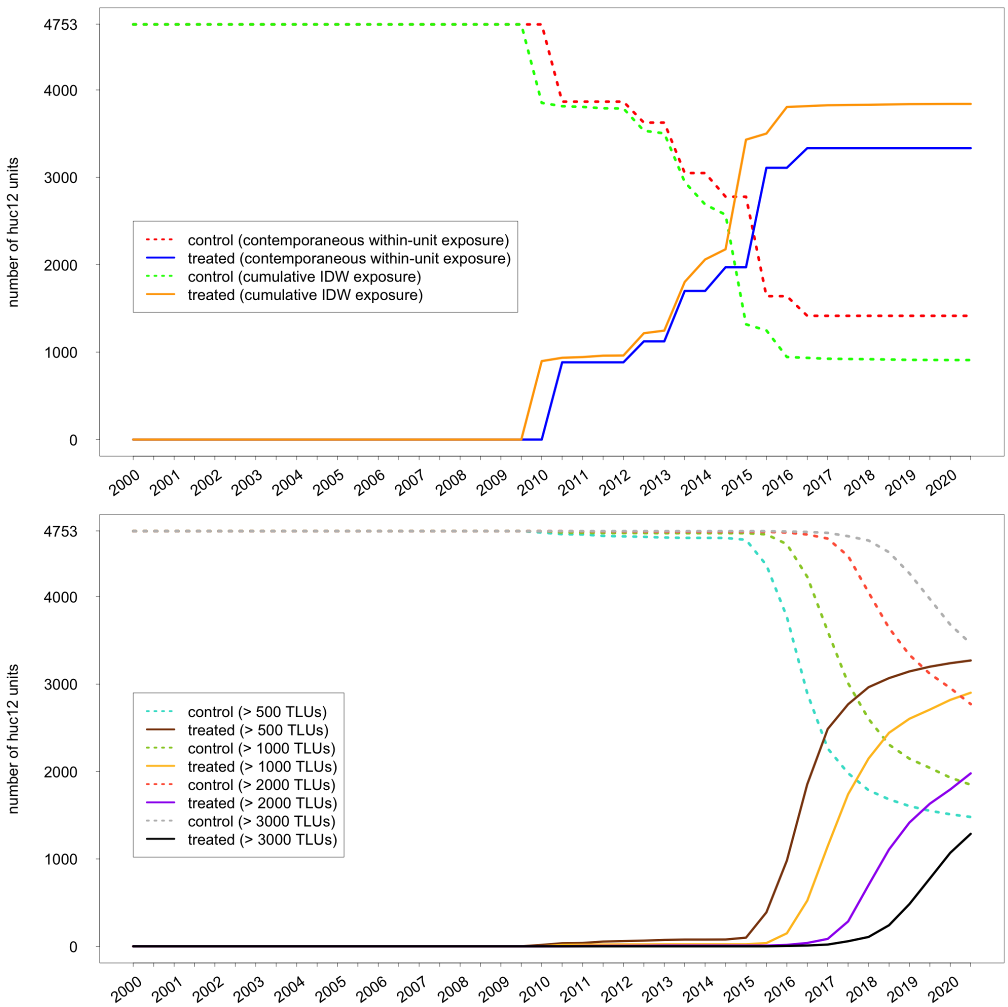

Figure 4: Top panel: Counts of extensive margin treated and control units over time at the HUC-12 level, contrasting contemporaneous IBLI exposure without IDW (contemporaneous within-unit exposure) and with cumulative IDW (cumulative IDW exposure). Bottom panel: Counts of treated and control units over time at the HUC-12 level for different intensive margins of exposure using IDW.

3.3 Rangeland condition measurement and other covariates

No unique measure of the health of rangelands exists; it is a latent variable. A widely adopted framework in rangeland science is rangeland health (RH), which is conceptualized as being 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 and/or impossible to gather retrospectively.

Remote sensing advances, however, now enable the development of validated RH indicators at scale (Reeves et al. 2015; Retallack et al. 2023).[9]

We use a combination of publicly available, remotely sensed data series and measures from Soto et al. (2024) who provide 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. 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 and forage quality over time and address potential aggregation bias from the modifiable areal unit problem (Openshaw and Taylor 1979; Avelino et al. 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).[10] We favor the enhanced vegetation index (EVI), which is widely viewed as an improvement over other similar indices but we study several for completeness.[11] 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, we create aggregate fractional cover and vegetation measures

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

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

[11]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.

within each areal unit using 30m resolution rangeland type maps from Soto et al. (2024). We use these maps to construct spatial masks, which we use as binary raster layers indicating usable pixels to capture rangeland variation of interest. Our main analysis relies on three spatial masks that permit study of 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.[12] 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. The final RH measures we employ are the proportion of each unit in each fractional cover class (BG, PV, NPV) and the mean vegetation index value for each time period and mask.[13] This combination of measures provides credible data on important variation in RH at scale. Appendix B.1 provides further details how these measures relate to the RH framework and standard ground-based approaches to measuring RH attribute indicators (Table B.1.1), summary statistics on fractional cover measures and EVI by each aggregated mask (all, high, and low) and three specific rangeland types to underscore underlying variation (Table B.1.2), and example maps of the three aforementioned rangeland masks (Figures B.1.1 - B.1.3).

Other time-varying natural processes impact RH, are likely to determine significant variation in biological productivity (Purevjav et al. 2025), and may be correlated with IBLI uptake. We therefore control for seasonal weather variation, which drives significant 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 et al. 1990). For temperature data we construct binned temperature exposure variables scaled to growing degree days (GDDs) 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 de-

[12]Soto et al. (2024) classify these rangeland types: 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' rangelands group, including CL since cultivated 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.

[13]For example, to gather a summarized vegetation index at an areal unit level for high forage quality rangelands in 2006, we apply the 'high' rangeland mask for 2006-2010.

viation of precipitation. Using these series, we construct control variables for each unit, year, season and level of aggregation over 2000-2020. Appendix B.1 provides summary statistics on these weather covariates by each level of aggregation (Table B.1.3).[14]

3.4 Trends in rangeland conditions

Figure 5 shows unconditional trends in the mean share of BG, PV, NPV, and the value of EVI for all rangelands, along with the contemporaneous trend in average precipitation. Analogous figures in Appendix B.2 show the contrasting trends across all, low, and high forage quality rangelands for fractional cover (Figure B.2.1) and EVI (Figure B.2.2). Figure 5 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 readily apparent. The corresponding figures in Appendix B.2 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. Overall, Figure 5 suggests that on average, BG and PV shares are slowly increasing while the NPV share is slowly declining. The apparent neutral trend in EVI also suggests that average biological productivity has held fairly constant in our study region over our study period, though subject to periodic, large swings in conjunction with variation in precipitation. These trends suggests some ambiguity as to whether rangeland conditions/health are improving or declining on average over time. Appendix B.2 features additional spatial and temporal variation in the unconditional values of these RH indicators via spatial animations at the HUC-12 level over 2000-2020 (Figures B.2.3 - B.2.5).

[14] 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.

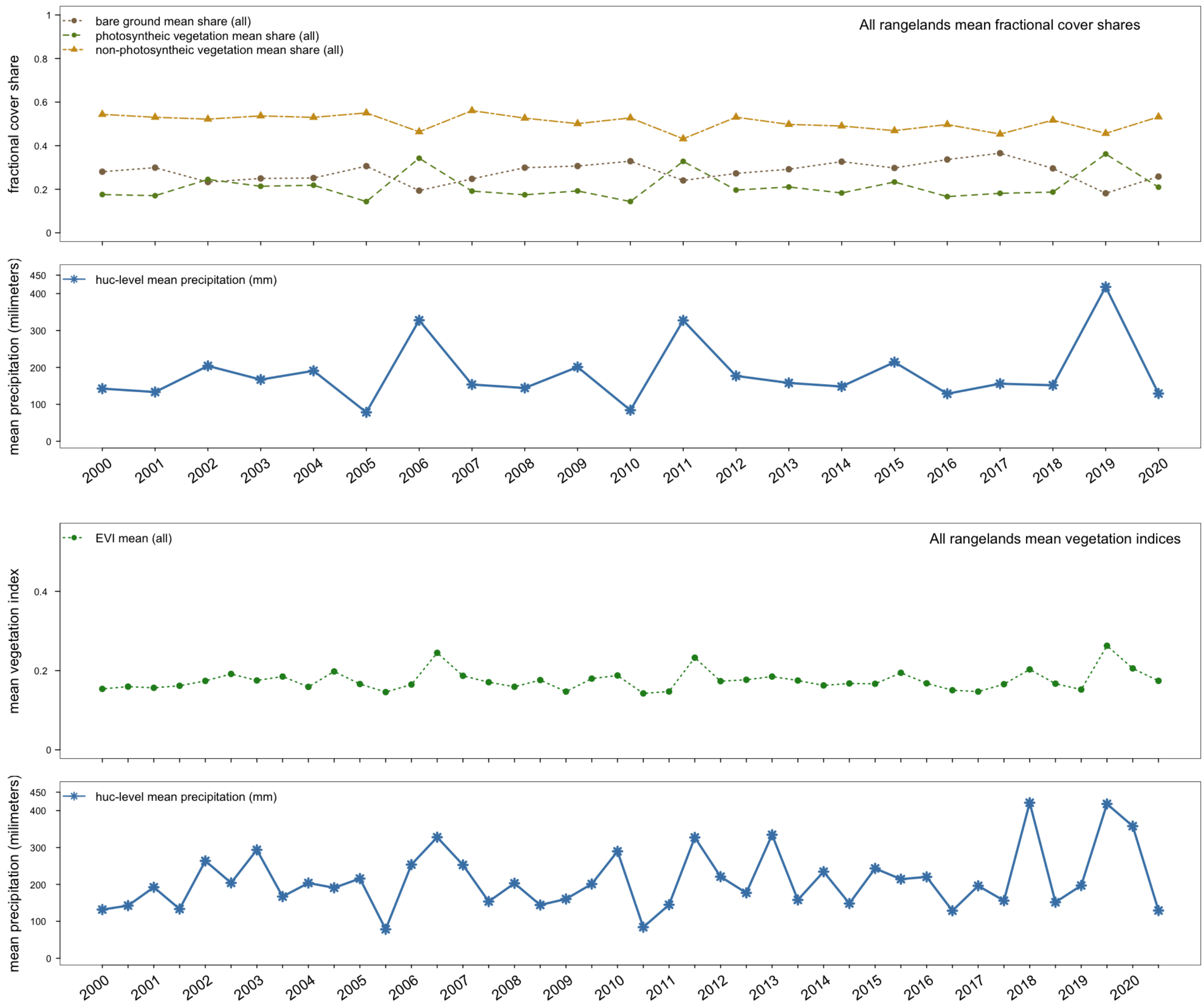

Figure 5: Trends at the HUC-12 level for mean fractional cover shares for all rangelands in the SRSD (top), mean precipitation in the SRSD (second from top), mean EVI in the SRSD and LRLD for all rangelands (third from top), and seasonal average precipitation in the SRSD and LRLD (bottom panel).

Figures 6 and 7 provide comparisons of average trends in RH indicators conditional on exposure to IBLI as measured via our IDW strategy (see Section 3.2). Figure 6 compares exposed and unexposed HUC-12 units at the extensive margin (i.e., a unit is exposed once $\geq$ 1 cumulative TLU is insured). Figure 7 compares exposed and unexposed HUC-12 units at the intensive margin where a unit is considered exposed once $\geq$ 500 cumulative TLUs are insured, which is very close to the mean cumulative exposure of 521 TLUs at the HUC-12 level over 2010-2020. Both figures depict variation in conditional average fractional cover share and conditional average EVI across all rangeland types. Analogous figures featuring comparisons in conditional average trends for all, high, and low groups are provided in Appendix B.2 at both the extensive margin and increasing levels intensive margin exposure for the HUC-12 level (Figures B.2.6 - B.2.9), and the same kind of variation is captured in companion figures at the HUC-8 level (Figures B.2.10 - B.2.13). The associated trends are very similar across masked variation (i.e., all, high, and low).

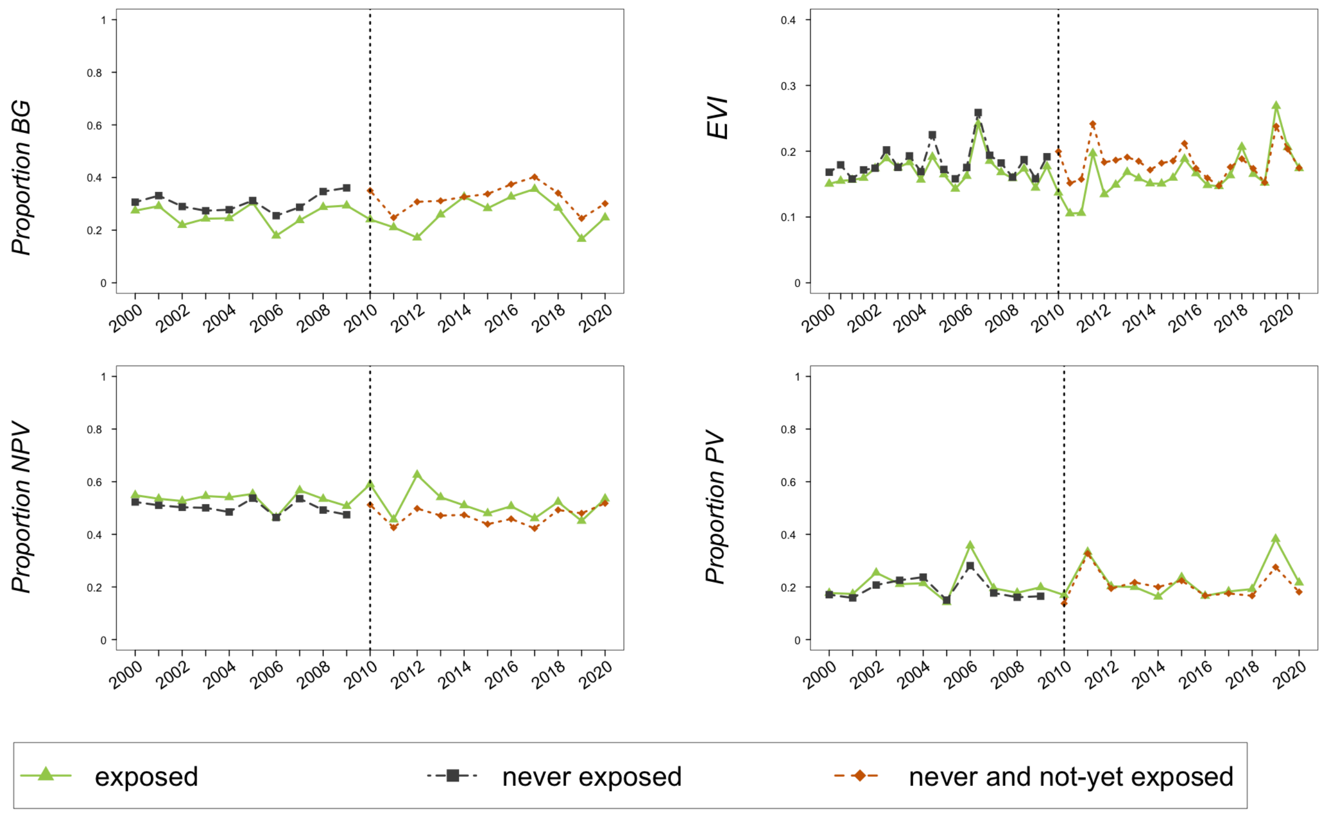

Figure 6: Extensive margin conditional trends in RH indicators measures across all rangeland types at the HUC-12 level; exposure is defined as ≥ 1 cumulative TLU insured. Vertical dashed lines indicate IBLI's 2010 launch. Top row: average proportion of bare ground (BG); average enhanced vegetation index (EVI). Bottom row: average proportion of non-photosynthetic vegetation (NPV); average proportion of photosynthetic vegetation (PV).

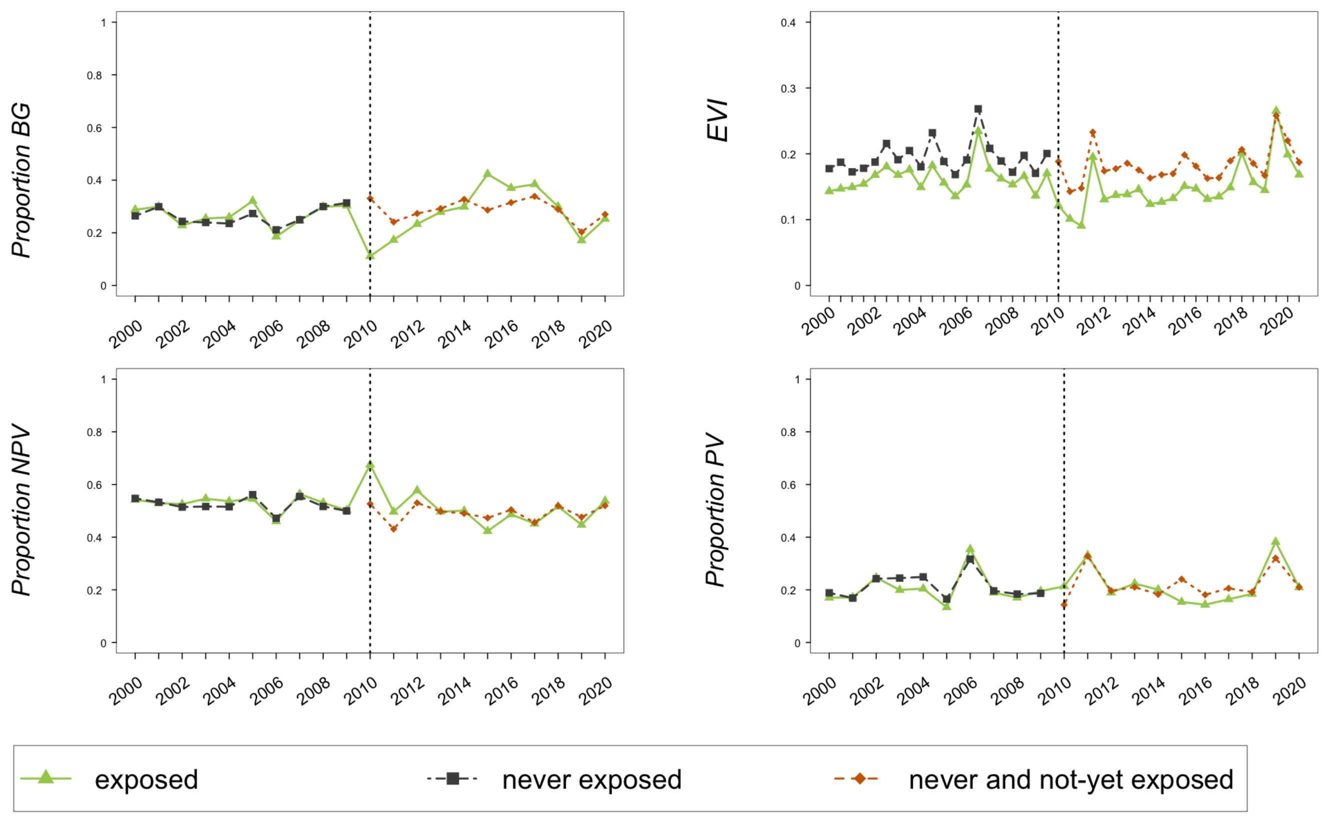

Figure 7: Intensive margin conditional trends in RH indicator measures across all rangeland types at the HUC-12; exposure defined as $\geq$ 500 cumulative TLUs insured. Vertical dashed lines indicate when the first HUC-12 units were exposed to $\geq$ 500 cumulative TLUs insured in 2010. Top row: average 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).

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 RH indicators, Figures 6 and 7 do provide very useful information. First, these figures show that exposed and never exposed averages followed very similar time paths prior to the 2010 launch of IBLI. Second, for a few indicators and years, observable differences seem to appear following exposure to IBLI, which are somewhat more apparent at the intensive margin (Figure 7). Overall, Figures 6 and 7 do not provide strong suggestive evidence of any significant pre-exposure deviations in trends, nor do they suggest a large impact on rangelands from IBLI. The lack of any discernible aggregate conditional trends also suggests that the fixed effect terms in the econometric estimation are not hiding or obviously controlling for some salient trend.

Another informative feature of variation captured in Figures 6 and 7, and the suite of companion figures in Appendix B.2, is that they demonstrate how event-time differs depending on the level of intensive margin exposure and level of aggregation. For example, at the HUC-12 level, the initial period of exposure can differ by several years with increasing levels of intensive margin exposure. For example, at the HUC-12 level, Figure B.2.7 shows intensive margin exposure at $\geq$ 500 cumulative TLUs first occurs in 2010, while Figure B.2.9 shows that exposure at $\geq$ 3000 cumulative TLUs first occurs in 2016. In addition, the initial year of exposure can also differ by level of aggregation for the same level of intensive margin exposure. For example, at the HUC-12 level Figure B.2.9 shows that exposure at $\geq$ 3000 cumulative TLUs first occurs in 2016, while Figure B.2.13 shows the the same level of exposure at the HUC-8 level first occurs in 2011. This perspective highlights how the underlying variation can differ spatially and temporally in staggered DiD estimation with varying levels of exposure and levels of aggregation.

4 Econometric Methods

Did the introduction and scaling of the microfinance product IBLI have unintended effects on the rangelands that support pastoralism? To motivate our staggered exposure estimation strategy to answer this question we first estimate standard two-way fixed effects (TWFE) specifications and implement tests for the appropriateness of TWFE (Jakiela 2021). These tests for the presence of negative weights and treatment effect heterogeneity confirm that TWFE is inappropriate in our setting (see Appendix C for details). 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 long-run changes in rangeland biological productivity (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., an extensive or intensive margin cumulative IDW exposure 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 $\mathbf{X}_{i,s,t}$:

$$Y_{i,r,s,t} = \mathbf{X'_{i,s,t}}\theta + \gamma_i + \sigma_t + \mu_{i,r,s,t} \tag{1}$$

where $Y_{i,r,s,t}$ reflects the pre-exposure RH outcome for areal unit i in rangeland type r in season s and IBLI-year t[15], vector $\mathbf{X'}$ includes measures of average precipitation and/or precipitation variability and binned hours of temperature exposure, γ_i and σ_t represent unit and time fixed effects, respectively, and μ captures the error term.

Step 2: Use the estimates of $\widehat{\theta}$, $\widehat{\gamma_i}$, and $\widehat{\sigma_t}$ from step 1 to residualize $Y_{i,r,s,t}$, defined as $\ddot{Y}_{i,r,s,t} \equiv Y_{i,r,s,t} - \mathbf{X'_{i,s,t}}\widehat{\theta} - \widehat{\gamma_i} - \widehat{\sigma_t}$, and regress it on treatment dummy D_{ist}:

$$\ddot{Y}_{i,r,s,t} = D_{ist}\beta + \ddot{\varepsilon}_{i,r,s,t} \tag{2}$$

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 heterogeneity of interest (e.g., specific group-time cohorts), including by time period for event studies. The event study version is obtained by replacing D_{ist} with a vector of event-time dummies $\mathbf{W'}_{ist}$ for testing pre-trends and 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

[15] 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.

2020). Garcia and Heilmayr (2024) and Alix-García and Millimet (2023) develop methods to mitigate these kinds of issues when outcome variables are binary at the pixel level. Since we use aggregated variables at an areal unit level as discussed in Section 3.3 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 Staggered Differences-in-Differences Results

5.1 Extensive Margin Tests

Figure 8 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 based on IDW at the extensive margin defined as ≥ 1 cumulative TLU insured at the HUC-12 level (see Section 3.2). All estimates include unit fixed effects and period fixed effects and time varying weather controls. All standard errors are clustered at the index unit level.

These findings indicate that 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 mean EVI. Specifically, we find a positive effect from IBLI exposure on mean 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 et al. 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 (see Section 3.3). Respective figures show extensive margin results with and without IDW across all the aforementioned rangeland subsets (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). Results shown in Figure 8 and in Appendix D.1 reflect nearly perfectly balanced panels at watershed unit levels where some marginal missingness reflects clouds or other quality filters for fractional cover and vegetation indices, and/or a few instances of very small units with odd geometry that did not intersect cleanly with larger pixels. Sample sizes also differ across rangeland forage quality masks because underlying rangeland types are not smoothly distributed in space.

The unbiasedness of these estimates depends on satisfying the parallel trends assumption during the pre-exposure period. Figure 9 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.

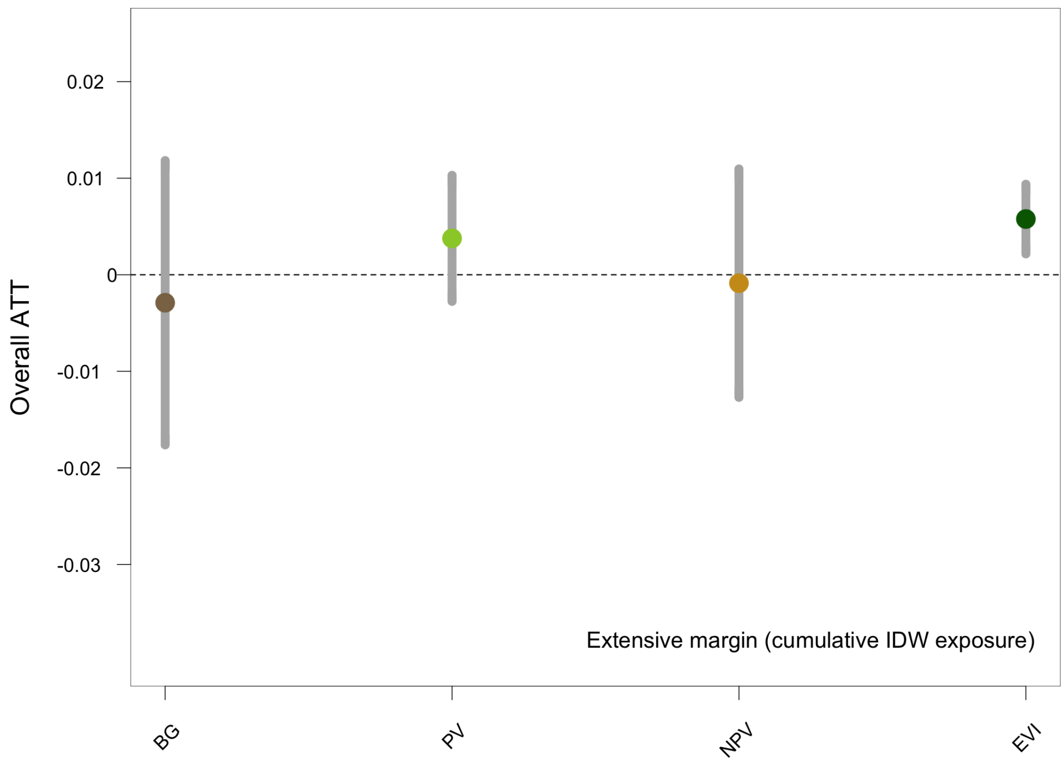

Figure 8: Overall ATTs with 95% confidence intervals for tests of impacts at HUC-12 level from IBLI exposure at the extensive margin based on cumulative IDW exposure (≥ 1 cumulative TLU insured). ATTs reflect point estimates of β in equation (2) (see Section 4). Standard errors are clustered at the index unit level. From left to right, estimated coefficients reflect IBLI's impacts on BG, PV, NPV and EVI within all rangelands (see Section 3.3). The number of observations for respective estimations are: fractional cover all mask, $n = 99,426$; EVI all mask, $n = 199,416$. 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.

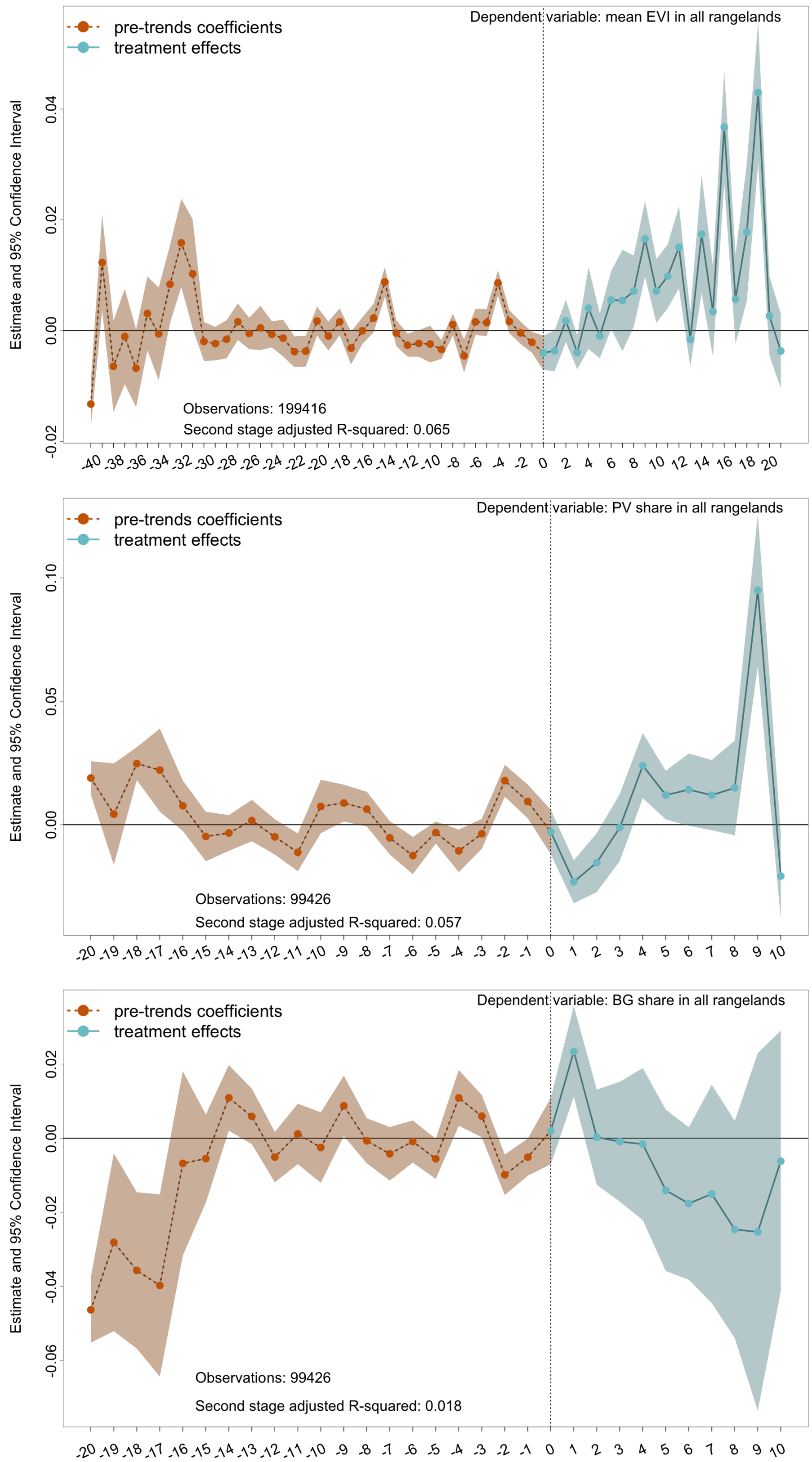

Figure 9: Event studies for the effect of IBLI at the extensive margin based on cumulative IDW exposure (≥ 1 cumulative TLU insured) on EVI, PV, and BG within all rangelands (see Section 3.3). Estimation is from an event study version of equation (2) (see Section 4). Standard errors are clustered at the index unit level.

Although most pre-exposure coefficient estimates are statistically insignificantly different from zero (Figure 9), 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. The earliest event-time coefficients are also likely to be more imprecisely estimated simply because there are few units within the earliest pre-trend periods.

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.

5.2 Intensive Margin Tests

We implement tests of IBLI's effect at the intensive margin using two complementary approaches supported by Gardner et al. (2025): continuous and binned. 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 10 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 TLUs, across all rangelands. Figure 11 provides the corresponding event studies for BG, PV, and EVI for all rangelands. All estimates include unit and period fixed effects and time varying weather controls. All standard errors are clustered at the index unit level. As with our extensive margin tests, our results featured here, and in Appendix D.2, reflect nearly perfectly balanced panels. Marginal amounts of missingness reflects clouds or other quality filters, and/or a few instances of very small units with odd geometry. Sample sizes also differ across rangeland masks because rangeland types are not smoothly distributed in space.

Both the binned and continuous approaches tell the same story, which is apparent via comparison of column 3 in Table 1 and the overall ATTs captured in Figure 10. 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 mean EVI measure. The binned exposure estimates also scale in a consistent manner with the continuous estimates. For example, the ATT for the effect on mean EVI in all rangelands at the $\geq$ 500 cumulative TLUs insured level is 0.011. 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. In addition, there are also indications of negative effects on BG and NPV, though these estimates are not consistently statistically significant.

The event studies captured in Figure 11 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.

To study additional variation at the intensive margin we conduct a variety of alternative specifications, including models with 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 (Tables D.2.1 - D.2.4). When unit-specific linear trends are included, 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 somewhat stronger. This approach is featured in column (3) of Table 1 and Figure 10.

The overall finding that emerges from these intensive margin results is consistent with our extensive margin findings. Specifically, the evidence points towards a neutral to positive effect of IBLI on rangeland conditions. Increasing greenness in both fractional cover and greenness is generally a encouraging finding, and potentially reduced BG is encouraging. These findings alone are insufficient to claim IBLI has a clear positive impact on RH, but the overall results are not consistent with the worst fears that IBLI might undermine rangeland systems and thereby induce the kinds of losses it is seeking to insure against.

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	99,426	99,426	99,426	99,426
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	99,426	99,426	99,426	99,426
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	99,426	99,426	99,426	99,426
Adjusted R^2	0.0007	0.001	0.004	0.00009
	Dependent variable: mean 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	199,416	199,416	199,416	199,416
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: Estimation is via a continuous exposure version of equation (2) (see Section 4). 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.

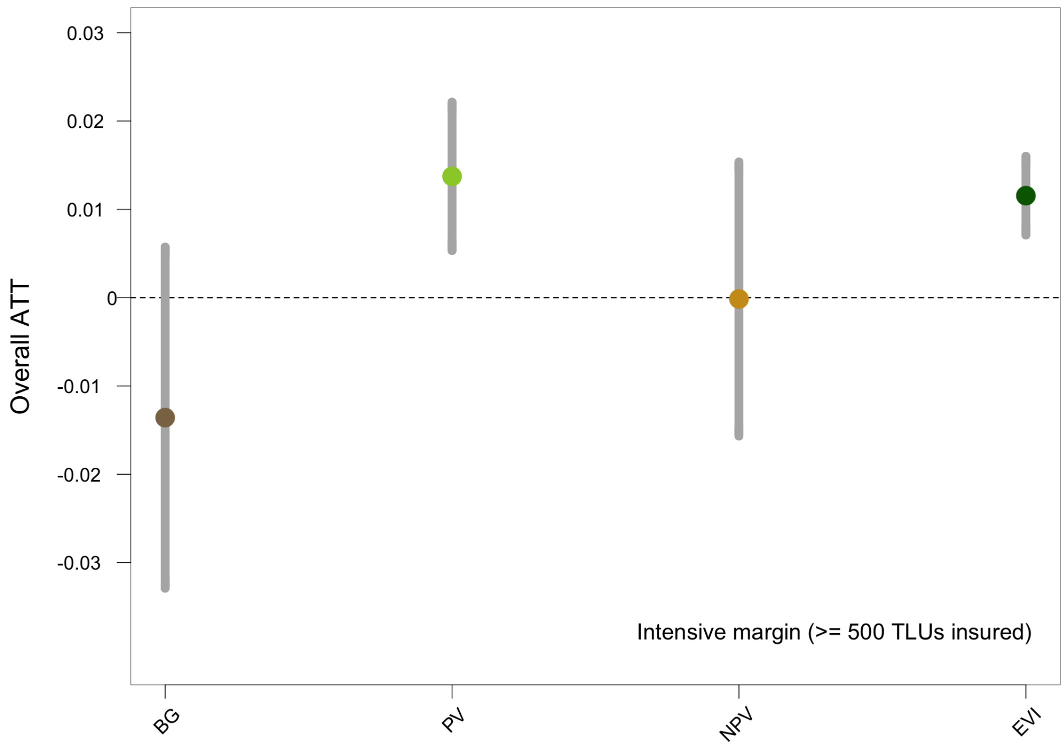

Figure 10: Overall ATTs with 95% confidence intervals for tests of impacts at HUC-12 level from IBLI exposure at the intensive margin of ≥ 500 cumulative IDW TLUs insured. ATTs reflect point estimates of β in equation (2) from Gardner et al. (2025) (see Section 4). Standard errors are clustered at the index unit level. From left to right, estimated coefficients reflect IBLI's impacts on BG, PV, NPV and EVI within all rangelands (see Section 3.3). The number of observations for respective estimations are: fractional cover all mask, $n = 99,426$; EVI all mask, $n = 199,416$. 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.

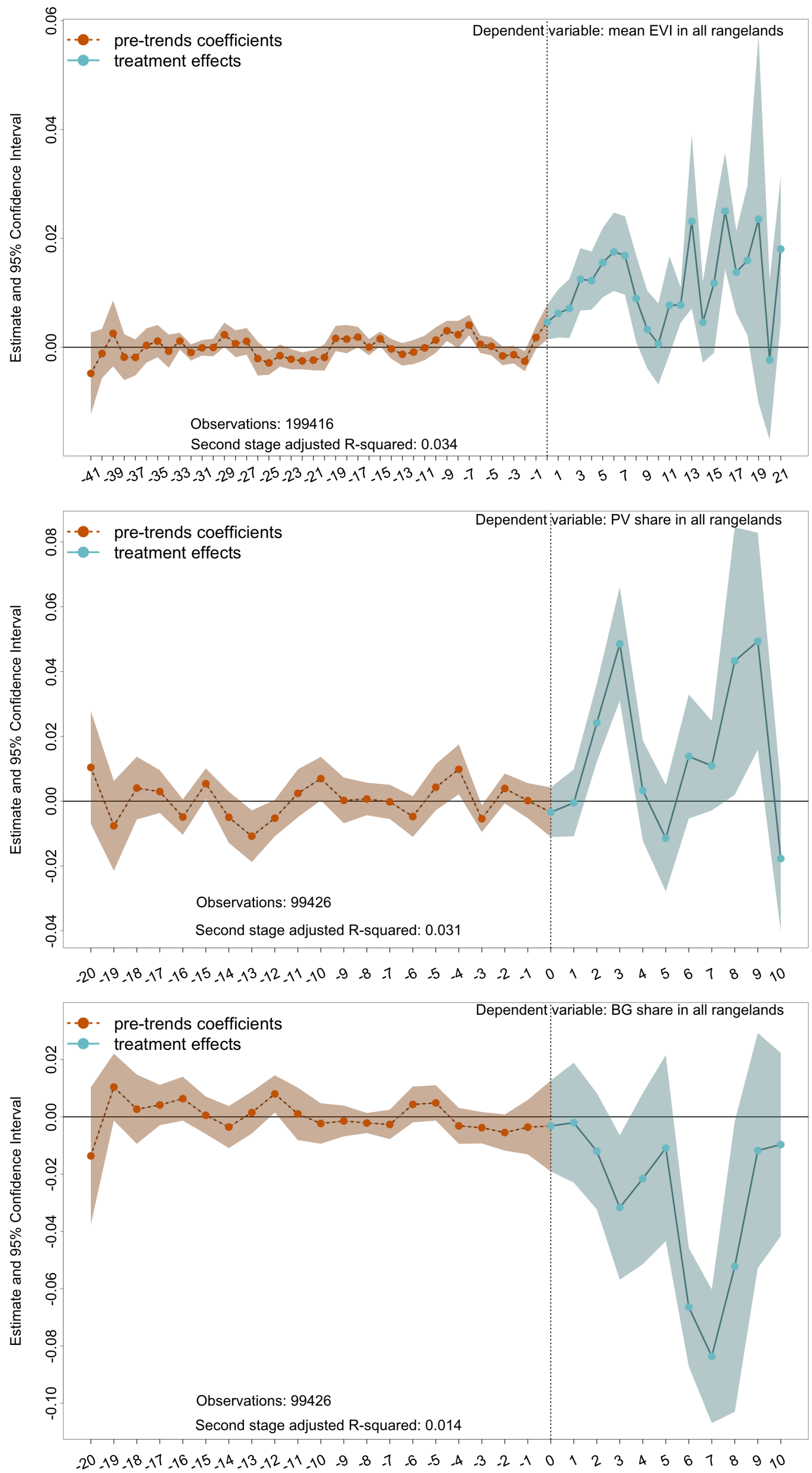

Figure 11: Event studies for the effect of IBLI at the intensive margin ($\geq$ 500 cumulative IDW TLUs insured) on EVI, PV, and BG within all rangelands (see Section 3.2). Estimation is from an event study version of equation (2) (see Section 4). Standard errors are clustered at the index unit level.

5.3 Robustness checks

Beyond the estimations referenced above, we implement three primary robustness checks to assess the stability of our core finding that IBLI has neutral to positive effects on rangelands. First, 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 overall ATTs in analogous fashion to Figure 10 focused on the same intensive margin exposure (i.e., $\geq$ 500 cumulative IDW TLUs insured) 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.

Second, 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 $\geq$ 1000, 2000, and 3000 cumulative IDW TLUs insured. Results at the $\geq$ 1000 cumulative TLUs insured level are comparable to those in Figure 10. At the $\geq$ 2000 cumulative IDW 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 $\geq$ 3000 cumulative IDW 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 our general findings and increasing intensive margin results are also generally consistent with neutral to positive impacts on rangelands from IBLI, 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 full 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 mean EVI withstand larger deviations from parallel trends than do our results for fractional cover measures.

5.4 Implications and potential mechanisms

The general pattern of impacts at the intensive margin on a continuous basis and above-mean IBLI exposure is consistent with, and 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 have 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. Such a determination would require a wider range of measures capturing a more credible suite of the elements that influence the three primary attributes of RH (Pellant et al. 2020). However, our findings allay widespread fears – and model-based simulations (Müller et al. 2011; John et al. 2019; Bulte and Haagsma 2021) – predicting that IBLI, or analogous livestock-focused index insurance, 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 et al. 2017; Toth et al. 2020; Barrett et al. 2025), which may have allowed rangelands to respond favorably to reduced grazing pressure. This is the extensive livestock grazing analog to findings from crop agriculture that support the Borlaug hypothesis that improvements in the returns to farming can reduce land degradation.

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 the case of microinsurance against catastrophic drought losses, the central premise is that insurance does not cause 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 et al. 2017, Matsuda et al. 2019, Barrett et al. 2025) and herding effort (Toth et al. 2020, Son 2025). We merge newly available, high quality data on East African rangelands health indicators and rangeland types over an extended period (Soto et al. 2024) with administrative data on IBLI exposure to 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. Rather, the evidence suggests neutral-to-positive impacts on rangelands, 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's 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 prove generalizable, that is, when microfinance expansion can be reasonably expected not to adversely impact the natural environment.

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