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ABSTRACT

Human-driven degradation of ecosystems threatens both global biodiversity and the livelihoods of communities that depend on natural systems for production and income. Yet empirical evidence on the economic returns to restoring nature remains scarce. We examine whether nature-enhancing interventions can generate measurable improvements in household wealth, in addition to environmental benefits. We study a large-scale agroecological intervention implemented by Trees for the Future (TREES) across farms in sub-Saharan Africa, combining detailed household surveys with high-resolution satellite imagery. We show that quasi-exogenous increases in natural capital lead to substantial gains in household wealth, proxied by livestock ownership, of about 75% by the third year of treatment. Each dollar invested in the intervention returns about $2.28 in direct wealth benefits for participating farmers, before accounting for positive health impacts and carbon sequestration. We further document dramatic increases in tree cover and crop diversity, significant improvements in food security and dietary diversity, and detectable enhancements in vegetation indices measured from space. Together, these results demonstrate that restoring natural capital generates both ecological and economic returns, offering a scalable pathway for nature-positive development in rural economies where biodiversity remains a critical productive asset.

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I. Introduction

Human activities are altering the Earth's ecosystems at an unprecedented pace, with profound consequences for climate and biodiversity. These threatened ecosystems underpin the global economy: roughly half of global GDP depends on nature and the ecosystem services it provides (United Nations Environment Programme, 2022). Low- and middle-income countries are particularly exposed to the risks associated with nature loss, as governments face difficult trade-offs between poverty alleviation and nature conservation.

While the environmental impacts of nature loss and ecosystem degradation are increasingly recognized, far less is known about the direct economic value that nature and biodiversity provide to human livelihoods and productive activity. Existing economic frameworks struggle to integrate ecosystem services—such as soil fertility, water regulation, and microclimate moderation—into measures of economic value, limiting both conservation policy and private investment in nature-positive pathways. This gap is especially acute in developing regions, where nature and biodiversity are central to agricultural livelihoods yet are rapidly depleted by unsustainable land-use practices.

One way to understand this gap is through the lens of capital accumulation. Economic development can be thought of as changing the portfolio of capital stocks that a country has. Developing countries start with a portfolio dominated by natural capital, and usually proceed by depleting natural capital and building up stocks of built, human and intellectual capital. This is the route followed by today's industrial countries. In this paper we examine an alternative route to development which involves building up selective types of natural capital rather than running them down.

Specifically, we examine whether the restoration and enhancement of nature through biodiversity-enhancing agricultural practices can generate measurable economic benefits for households in rural Eastern and Western Africa. Drawing on detailed data from a biodiversity-enhancing, nature-based agricultural intervention (hereafter, natural capital intervention) implemented across rural communities, we adopt a quasi-experimental design to estimate the causal impact of pro-nature investments on household wealth and farm productivity.

Our analysis combines detailed household- and farm-level data from Trees for the Future (TREES) with high-resolution satellite observations to quantify how the natural capital interventions shape household finances across five countries in sub-Saharan Africa. TREES is a nonprofit organization that trains farmers in Eastern and Western Africa in sustainable farming practices that increase the farms' natural capital. Some of these practices include increasing the agro-biodiversity of the crops planted and the number of trees on the farm. Our collaboration with TREES yields rich information on demographic characteristics, agricultural practices, livestock ownership, crops planted, trees planted, food security, and geolocated farm attributes for 5,414 smallholder farms between 2017 and 2024. We complement these microdata with satellite-based estimates of biomass for 49,982 farms using Sentinel-2 imagery to compute the Enhanced Vegetation Index (EVI), a biophysical indicator of vegetation density and health measured at 10 m resolution.[1] This integration of ground-level and remote-sensing information allows us to trace the evolution of natural capital on farms and link it to economic outcomes at an unprecedented level of spatial and temporal granularity.

To estimate the causal effects of the intervention, we employ a stacked difference-in-differences framework that exploits the staggered roll-out of the program across project areas. Specifically, we implement a within-household estimation strategy to assess how changes in biodiversity affect financial, environmental, and welfare outcomes. In essence, we compare each treated farm's outcome before and after the natural-capital-enhancing intervention. The empirical design incorporates farm fixed effects to control for time-invariant heterogeneity—such as climate, soil quality, household structure, and land size—and country-year-month fixed effects to absorb region-specific economic shocks and differences in survey timing. Our baseline outcomes rely on livestock ownership, a widely used proxy for household wealth in rural economies, and are complemented by measures of direct income data for a subsample of farms.

The baseline estimates reveal substantial and steadily growing improvements in household wealth following the intervention. Across all specifications, treated farmers become significantly

[1] The sample of 49,982 farms, relative to the baseline sample of 5,414 farms, includes both participating farms for which only limited information is available (location and year of treatment) and randomly selected control farms that do not participate in the TREES program.

more likely to own livestock, with the probability rising by 22%, 38%, and 75% in years 1, 2, and 3, respectively. Intensive-margin effects are also economically significant: by year 3, livestock holdings increase by roughly 26 units or 3.8 times the baseline average (6.6 times the baseline median), underscoring the cumulative financial benefits of enhanced natural capital. Next, we investigate possible channels driving the results. Specifically, first, we find that the intervention successfully increases dramatically the number of trees, marketable crops, and food crops per farms. These patterns, robust across multiple specifications, confirm that the program generates pronounced ecological gains. The magnitude and timing of these improvements provide evidence that the observed increases in household wealth operate through the intended channel of restored natural capital rather than through unrelated contemporaneous shocks. Moreover, we find that the increase in the livestock units is positively related to these three natural capital indicators, further suggesting that natural capital is an important channel driving the increase in wealth. Taken together, the results show that ecological restoration translates into meaningful economic and environmental gains in settings where livestock functions both as a source of income and a key store of wealth.

To validate the identifying assumptions and provide further robustness, we estimate a dynamic difference-in-differences (DiD) model using EVI as an outcome, constructing geospatially matched control sites and finding that treated and control farms follow statistically indistinguishable vegetation trends prior to program entry. In addition, we find that the increase in the treated farms' natural capital is perceptible via satellite, with an increase in EVI post-treatment of about 3% of the sample mean.

Beyond financial and environmental outcomes, we document that natural capital gains translate into broader improvements in well-being. Using standardized indicators from the Household Food Insecurity Access Scale (HFIAS), we report large and statistically significant reductions in severe food insecurity and episodes of running out of food, alongside meaningful increases in dietary diversity. These health-related improvements are consistent with the program's focus on diversifying crops, stabilizing yields, and strengthening agroecological resilience, and they reinforce the link between ecological restoration and human development. Finally, in a complementary matched-sample analysis using direct income data, treated households exhibit substantially higher income and crop consumption, further underscoring the project's positive impacts on food security and household wealth.

Overall, this multi-scale dataset and empirical approach allow us to isolate the effects of natural capital improvements on household finances and health. By showing that ecological restoration can generate measurable gains in vegetation, reduce food insecurity, and enhance economic well-being, the study provides new evidence that nature-based interventions can simultaneously strengthen rural livelihoods and promote ecosystem recovery at scale. Moreover, the insights from the study are not only valuable for African farmers but also any rural farmers worldwide, as nature-positive interventions can break the conventional trade-off between environmental and economic objectives, offering a scalable model for global sustainable rural development that aligns conservation with economic value.

This study contributes to a rapidly growing interdisciplinary literature on natural capital, biodiversity, and economic outcomes. While prior research has theorized that natural capital, including natural ecosystems and biodiversity, underpins economic activity providing valuable services, empirical micro-level evidence has been relatively scarce (Hotelling, 1931; Stiglitz, 1974; Drupp et al., 2024; Giglio, Kuchler, Stroebel, and Wang, 2024). For example, Frank and Sudarshan (2024) estimates the economic value of vultures in India, documenting a causal link between vulture population decline and a significant increase in mortality. Similarly, Frank (2024) shows how biodiversity loss affects human health by studying the white-nose syndrome affecting bats. Our analysis complements this literature by directly linking increases in natural capital to improvements in household wealth, thereby addressing a critical empirical gap in the emerging literature on biodiversity and economic development.

In doing so, we respond to recent calls for more rigorous studies on the economic value of biodiversity, particularly in vulnerable economies (Karolyi and Tobin-de la Puente, 2023; Giglio, Kuchler, Stroebel, and Wang, forthcoming). Our study also contributes to the nascent but growing literature on biodiversity finance, which examines how financial instruments and blended capital structures can mobilize private and public funds to conserve and restore natural systems, and how investments in biodiversity can be assessed along dimensions of risk, return, and ecological impact

(Chen et al., 2023; Bahrami, Gustafson, and Steiner, 2024; Garel et al., 2024; Flammer, Giroux, and Heal, 2025; Giglio, Kuchler, Stroebel, and Wang, 2025; Giglio, Kuchler, Stroebel, and Zeng, 2026)

Finally, our results underscore the importance of natural capital for household wealth and development economics. Whereas much of the finance literature examines credit, savings, or asset accumulation in urban or developed markets, our study centers on rural African communities where natural capital plays a crucial role in economic resilience and wealth accumulation (Taylor and Druckenmiller, 2022; Rizzi and Lewis, 2022). We show that enhancing natural capital can serve as an effective development intervention in its own right. This finding broadens the perspective of household finance by incorporating environmental factors into the discussion of wealth building and resilience. It also bridges to the rural development literature by providing evidence that natural capital interventions can yield significant economic dividends for smallholder farmers.

In sum, by combining high-resolution remote sensing with longitudinal household data, we bridge gaps between conceptual natural-capital frameworks and empirical assessments of livelihood impacts in frontier contexts. Moreover, our work highlights biodiversity as an integral component of financial and economic development strategies in vulnerable regions informing policy decisions, development programs, nonprofit organizations, and donors, ultimately contributing to economic stability and improved livelihoods in rural communities.

The remainder of the paper is organized as follows. Section II describes the natural capital intervention. Section III provides a description of the data and summary statistics. Section IV, V, and VIII present the empirical approach, results, and additional tests. We conclude in Section IX with a brief summary.

II. The Natural Capital Intervention by TREES

Trees for the Future (TREES) is a nonprofit organization working with farmers to implement a natural capital intervention that restores degraded soil, fosters healthy ecosystems and biodiversity, and improves household food and income security. Their intervention lasts four years in which TREES staff provide seeds and trains farmers on specific tools and practices, including but not limited to crop diversification, composting, and water retention. A central component of the intervention is the Forest Garden Approach, an integrated agroforestry system that combines trees, food crops, and marketable crops on the same plot to enhance on-farm natural capital and economic resilience. As part of this approach, they help farmers plant fast-growing trees around the perimeter of their land to create a living fence that protects crops, stabilizes soils, and infiltrates water into the ground. Farmers are also provided with vegetable seeds to establish permagardens to develop economic resilience through the growing and harvesting of a multitude of crops that will provide more consistent yields throughout the year as compared to conventional monocultures lacking diversification.

One of the main objectives of the intervention is for farmers to have something to eat and sell each month of the year (as opposed to once or twice a year with staple crops like maize). The living fence also provides natural resources needed for the farmer, particularly a sustainable source of fuelwood for cooking, and animal fodder (from tree leaves).[2] Figure 1 presents a schematic overview of the intervention and its associated economic, environmental, and health outcomes. As of December 2025 and since 2014, TREES has planted 420,110,579 trees collaborating with 63,767 farmers in Kenya, Mali, Senegal, Tanzania, Uganda, Central African Republic, and Guinea (Trees for the Future, 2025).[3]

We note that the intervention by TREES is not a randomized control trial (RCT) often viewed as the gold standard when assessing interventions of this type. Farmers join the program through various self-selection mechanisms such as word of mouth, community workshops, and local outreach efforts. This means that participation is not randomly assigned, which could introduce selection bias into our estimates. It could be argued that both the lowest performing and best performing farmers would be more likely to participate. The lowest performing might join as they have nothing more to lose. The best performing, as they have a more stable income, might have further incentives

[2] Table IAII in the Internet Appendix contains the full list of items received by the farmers over the 4 years of the project.

[3] For reference, in the three Kenyan counties where TREES has operated (Homa Bay, Kisumu, and Migori) and we have data, the total number of farming households in 2019 was 519,507, compared with 24,502 farmers participating in the TREES program.

in participating to test new approaches on a portion of their land. Moreover, in order to participate in the TREES program, farmers must have secure land tenure and a reliable water source nearby. Accordingly, our estimates should be interpreted as the effect of the intervention for households that meet these participation criteria.

To address the non-random selection and strengthen the validity of our causal inferences, we utilize different approaches described in Section IV that allow us to control for observable and unobservable factors that might influence both participation in the program and financial outcomes. Furthermore, using TREES data is considerably more cost and time-efficient than conducting an RCT, enabling us to perform a robust analysis within practical constraints in a relatively short time period.

III. Data and Summary Statistics

A. Household and Local characteristics

To investigate the impact of biodiversity on household finances in African agricultural communities, we draw on multiple datasets provided by the non-profit organization Trees for the Future (TREES). This collaboration grants us access to rich, multi-dimensional data encompassing household economic and demographic characteristics, as well as detailed farm-level information across several regions in Africa. The scope and granularity of these datasets enable an analysis that would otherwise be prohibitively expensive to conduct independently or through a randomized controlled trial.

The first dataset is a household-level panel that includes information on household composition, farm size, geographic coordinates, livestock ownership, food security, dietary diversity, and trees and crops planted. This panel contains 6,052 farm-year observations for 5,414 farms located in Kenya, Senegal, Tanzania, and Uganda, surveyed between 2017 and 2024. We use this dataset for the main empirical analysis. Table I reports summary statistics for the key variables.

The second dataset covers a larger sample of farmers (24,991) but contains a more limited set of variables, namely farm location and the number of trees and crops planted before and after the intervention. These farms are located in Guinea, Kenya, Mali, Senegal, Tanzania, and Uganda (Figure 2). We augment this dataset with randomly selected control farms drawn from the same geographic areas in which the intervention took place. The resulting panel includes 355,440 farm-year observations for 49,982 farms over the period 2017–2024 and is used primarily to study changes in natural capital and vegetation outcomes.

The third dataset is the smallest in terms of sample size but contains the richest economic information, including direct measures of household income and expenditures. This dataset is cross-sectional and covers 430 farms. Across all analyses, we complement the TREES datasets with satellite-based estimates of local gross domestic product at the $0.25^\circ \times 0.25^\circ$ grid-cell level from Rossi-Hansberg and Zhang, 2025. These Gross Cell Product (GCP) measures allow us to control for time-varying local economic conditions.[4]

Finally, our collaboration with TREES provides qualitative insights that complement the quantitative analysis. Their operational expertise ensures that our empirical approach reflects on-the-ground realities in the study regions, enhancing the interpretation of the results and the relevance of the policy implications.

B. Enhanced Vegetation Index

To quantify changes in on-farm natural capital, we use the Enhanced Vegetation Index (EVI), a satellite-derived measure of vegetative "greenness" that is particularly well suited for smallholder agricultural landscapes. EVI improves upon the Normalized Difference Vegetation Index (NDVI) by enhancing sensitivity in areas with dense vegetation and correcting for atmospheric and canopy-background noise. It is computed as follows:

$$\text{EVI} = G \times \frac{(\text{NIR} - \text{RED})}{(\text{NIR} + C_1 \times \text{RED} - C_2 \times \text{BLUE} + L)}, \tag{1}$$

[4] Table IAI provides definitions for the variable utilized in the paper.

where NIR, RED, and BLUE denote surface reflectance in the near-infrared, red, and blue bands; (L) is a canopy background adjustment; (C_1) and (C_2) are aerosol-resistance coefficients; and (G) is a gain factor.[5]

We compute EVI using Sentinel-2 Level-2A imagery, which provides 10 m spatial resolution in the relevant spectral bands. This resolution is well matched to the study context: with farms averaging roughly 1 hectare, Sentinel-2 yields dozens of within-farm pixels, allowing us to characterize vegetation dynamics at a scale meaningful for household production decisions. To improve measurement quality, we impose a scene-level cloudiness threshold of 80 (i.e., scenes with estimated cloud cover above 80% are excluded). Although relatively permissive, this filter ensures that scenes containing usable cloud-free patches over the small farms are retained while avoiding the systematic temporal gaps that stricter thresholds would introduce in tropical and subtropical settings. This approach maximizes temporal coverage—crucial for capturing within-season crop dynamics—while maintaining a sufficient signal-to-noise ratio in the vegetation index.

IV. Empirical Approach

A. Sample Information

Farmers join the program during the mobilization process. After selecting a new project zone and getting approval and information on farming communities from local authorities, community meetings are held to sensitize potentially interested farmers in the program. Usually a couple of meetings will occur in a village to make sure there is a clear understanding on the project and each parties expectations. A sheet for those wanting to join the program is left with village leader for sign up and collected at a later date. TREES staff then collects this sheet with contact information and begins assessing if the farmer follows the criteria for the program (farmer must have secure land tenure and have a reliable water source nearby). If the criteria is met, the farmer will be registered with a Forest Garden ID and GPS coordinates of the field are recorded.[6]

[5]For Sentinel-2 and MODIS implementations, the standard parameter values are (G = 2.5), (L = 1), (C_1 = 6), and (C_2 = 7.5).

[6]Additional details about the intervention are provide in Section I of the Internet Appendix.

An important eligibility criterion for participation in the TREES program is secure land tenure. To provide context on baseline tenure conditions in the study countries, we draw on data from the Prindex, which measures perceived tenure security and documentation of land and housing rights.[7] In Kenya and Tanzania, approximately one-third of individuals report feeling insecure about their land and property rights, while 65–75% report possessing formal or informal documentation of home ownership or use. In Uganda, reported tenure insecurity is somewhat lower, at around one-quarter of the population, with roughly 60% holding documentation. Senegal exhibits the lowest levels of perceived tenure insecurity, at about 20%, and the highest documentation rates, close to 90%. Although these measures capture perceived tenure security and documentation rather than legally registered agricultural land titles, they suggest that secure land tenure is not universal across rural populations. As a result, the land-tenure requirement for TREES participation likely restricts eligibility to a subset of farmers with relatively stronger baseline tenure security, an important consideration for interpreting external validity and scalability.

Another key eligibility requirement for participation in the TREES program is reliable access to water resources. Direct, nationally representative data on agricultural water access among smallholder farmers are limited. However, available household-level statistics provide useful context on baseline water access conditions in the countries studied. In Kenya, approximately 56% of rural households have access to at least basic water services. In Tanzania, recent census data indicate that around 70% of households use an improved water source, though rural access has historically lagged behind urban areas.[8] In Uganda, rural access to safe water supply is 67%, while Senegal exhibits higher overall access to improved water sources, at roughly 86%, with rural areas still trailing national averages. We note that the rest of the households in these countries still have access to water even though not covered by improved water source usually through wells and surface water. Although these measures do not directly capture irrigation or farm-level water infrastructure, they suggest that secure water access is neither universal among rural households nor restricted to only a small minority.

[7] More information available on https://www.prindex.net/data/.

[8] According to the World Bank definition, improved water sources include piped water into dwelling, plot or yard; piped water into neighbor's plot; public tap/standpipe; tube well/borehole; protected dug well; protected spring; and rainwater.

Given the possibility of selection bias, we examine whether our sample differs systematically from an external benchmark survey. Specifically, we use nationally representative data for Tanzania from the World Bank's Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA).[9] We focus on the fifth wave of the survey, as it is the only wave that overlaps with our sample period (2020–2021). Tanzania is selected because it is the only country in which an LSMS-ISA survey was conducted during a period and in regions comparable to the TREES program.

Table IAIII in the Internet Appendix compares baseline household and farm characteristics between TREES participants and rural households from the World Bank survey in Tanzania. Because participation in the TREES program is voluntary rather than randomly assigned, these differences are informative about potential selection into the intervention. Overall, TREES farmers appear different from the broader rural population along several observable dimensions. Participating households have more children, particularly young children, and report higher levels of food insecurity. At the same time, TREES farmers exhibit higher educational attainment and are substantially more likely to report farming as their primary source of income. Farm characteristics also differ meaningfully: TREES farms are smaller in land area and have significantly fewer trees. The number of livestock differs sharply across samples, though these comparisons are conditional on ownership and reflect the differing survey structures.[10]

Taken together, these patterns suggest that TREES participants are neither a random subset of rural households nor exclusively the most advantaged farmers. Instead, they appear to be households that are highly engaged in agriculture, face meaningful food-security challenges, and operate relatively small farms. These systematic differences underscore the importance of our empirical strategy, which relies on within-household variation and fixed effects rather than cross-sectional comparisons, to address concerns that observable and unobservable characteristics may jointly influence both participation and outcomes. At the same time, the descriptive differences highlight that the external validity of the results should be interpreted in light of the program's eligibility criteria and voluntary enrollment structure.

[9] More information is available at https://www.worldbank.org/en/programs/lsms/initiatives/lsms-ISA#7.

[10] The World Bank survey collects information for a separate sample when analyzing livestock.

B. Identification Strategy

TREES aims to improve household welfare through a combination of practices, including increasing crop diversity and planting trees around farms. These practices affect multiple dimensions of on-farm natural capital; most importantly, they improve soil quality by enhancing nutrient retention and water-holding capacity. Farmers join the program through various self-selection mechanisms, such as word of mouth, community workshops, and local outreach efforts. Participation is therefore not randomly assigned, raising the possibility of selection bias in the estimates as discussed above.[11]

To address non-random program participation and strengthen the validity of our causal inferences, we employ a fixed-effects framework that controls for both observable and unobservable factors that may jointly influence participation and financial outcomes. While we do not implement a proper RCT, the TREES data enable a rigorous quasi-experimental analysis that exploits within-farm variation over time without additional waiting periods and expenses.

We employ a stacked difference-in-differences (DiD) model where the control group includes farms that have not yet received the treatment, but have agreed to participate. All observations in the following years are treated observations. The model is specified as follows:

$$y_{i,c,p,t} = \sum_{\ell=1}^{\ell=+3} \gamma_\ell \, Treat^{\ell}_{i,c,t} + \lambda' X_{i,c,p,t} + \tau_i + \rho_{c,t} + \varepsilon_{i,c,p,t}, \tag{2}$$

where i represents a farm in province p of country c in year t.

We estimate both the extensive and intensive margin effects of the intervention, measured relative to the year in which a farm enters the program. For the extensive margin, the outcome variable is an indicator equal to one if the farm owns any livestock. For the intensive margin, the outcome is the natural logarithm of the number of livestock animals.

$Treat$ is an indicator equal to one in each year following a farm's entry into the program. The

[11] Both relatively low-performing and high-performing farmers may be more likely to enroll. In addition, participation in the TREES program requires secure land tenure and reliable access to water. As a result, at a minimum, our estimates should be interpreted as the effect of the intervention for farmers who meet these eligibility criteria.

baseline year (Year 0) contains pre-treatment information on farm characteristics and serves as the reference period. In the baseline specifications, the vector of control variables X includes the change in local Gross Cell Product (GCP) measured at the $0.25° \times 0.25°$ grid-cell level using satellite-based estimates from Rossi-Hansberg and Zhang (2025). This control accounts for time-varying local economic conditions that could otherwise confound the estimates.

All specifications include farm fixed effects, which absorb time-invariant farm characteristics, such as land size, household composition, and altitude. We also account for aggregate shocks at the country level as well as differences in the timing of survey implementation that may affect outcome measurement using country–year–month fixed effects.[12] Standard errors are clustered at the project-area level—the level at which treatment is delivered, field teams operate, and correlated shocks are most likely to arise.[13] Anticipation effects are minimal in this setting. Although the parallel-trends assumption cannot be directly tested for the primary outcomes due to data limitations, the stacked design and the inclusion of farm fixed effects mitigate concerns related to differential pre-treatment trends. We formally assess the parallel-trends assumption in Section V.A using satellite-based vegetation outcomes from the second dataset described in Section III.A.

In the baseline estimates, we use livestock ownership as a proxy for household wealth for both practical and conceptual reasons. First, direct measures of income and expenditures are available only for a subset of farmers and only in a cross-sectional setting. In contrast, data on livestock ownership are observed for nearly all households over time, providing a consistent and reliable measure that supports robust panel-based analysis. Moreover, prior studies have used livestock ownership as a proxy for wealth or have examined the effects of livestock transfers in RCTs to generate exogenous shocks to household assets (e.g., Banerjee et al., 2015).

From a conceptual perspective, livestock ownership is a strong indicator of household wealth and income in agricultural economies. Livestock contributes to rural livelihoods and employment, serves as a buffer against income shocks, and functions as a form of savings and insurance (Schmidt, 1992; Moll, 2005; Alary, Corniaux, and Gautier, 2011; Pica-Ciamarra et al., 2011; Upton, 2004).

[12] We also estimate specifications with farm, country–year, and country–month fixed effects.

[13] At project initiation, TREES typically enrolls approximately 60 farmers within a defined geographic area. Residual correlation is therefore likely at the project-area level. Results are robust to clustering at larger geographic units.

In addition, livestock represents a form of productive capital that households can acquire only when they have sufficient financial resources, allowing livestock to function as a store of value. This dual role—both as a productive asset and as a savings vehicle—makes livestock ownership a meaningful and contextually appropriate measure of economic wealth. Finally, the intervention studied here does not directly provide farmers with livestock or cash transfers; instead, households must use their own resources to purchase animals. Consequently, observed changes in livestock ownership are likely to reflect changes in household income and economic well-being rather than mechanical effects of the intervention itself. By focusing on livestock ownership, we can capture broader economic trends and household responses to natural capital improvements.

C. Baseline Estimates

Table II and Figure 3 present the effects of natural-capital enhancements on livestock ownership at both the extensive and intensive margins. At the extensive margin, we find a positive and statistically significant effect of the intervention on the likelihood that a household owns any livestock over the three post-treatment years. In the most stringent specification, which includes farm and country–year–month fixed effects (column (2)), the probability of livestock ownership increases by 22%, 38%, and 75% in years 1, 2, and 3, respectively, relative to the baseline year.

At the intensive margin, the results are consistent when using the number of livestock animals as the outcome variable, as shown in Table II columns (3)–(4) and Figure 3, Panel B. By the third year of treatment, treated farmers own approximately 25 additional animals relative to baseline. The findings are qualitatively similar when using the natural logarithm of livestock holdings as the outcome (Table II columns (5)–(6)) and are stronger when excluding farm fixed effects and including pre-treatment household characteristics and city- or province-level fixed effects (Table IAIV).[14]

Across all specifications, the coefficients increase in economic magnitude over time, suggesting a cumulative effect of natural capital improvements on livestock ownership. This temporal pattern aligns with expectations that the intervention enhances ecosystem services, such as soil quality,

[14]Household characteristics include an indicator for whether the household head is the most educated member or female, the age of the household head, household size, and farm size. Results are also robust when livestock holdings are scaled by land area (Table IAIV, columns (5)–(6)).

water retention, pest control, and resilience to climatic shocks, which increase farming income and farmers' wealth. Overall, the findings provide evidence that the intervention positively influences livestock ownership on the extensive and intensive margins. These results highlight the role of natural capital in increasing household wealth, particularly in rural communities where livestock plays a central role in household savings and risk management.

V. Channel: Increase in Natural Capital

To highlight that the impact on household finances is related to the intervention and not unobservable and contemporaneous events, we report direct measures of success in increasing farms' natural capital. Specifically, we test whether the intervention has an impact on the farms' number of trees, marketable crops, and food crops: the main items TREES focuses on. Baseline values for the number of trees and marketable crops are often very low, with many farms reporting zero or one tree or crop in the pre-treatment year. In such cases, log specifications can behave poorly, because moving from (almost) zero to several trees or crops generates mechanically large relative changes and undefined values at zero. To address this issue, our main specifications use winsorized levels.[15]

Because the intervention introduces hundreds or even thousands of trees into farms that begin with only a handful—or none at all—we expect very large estimated effects. In line with our expectations, the results reported in Table III and Figure 4 show an economically and statistically significant increase in all three outcome variables. The number of trees increases dramatically by about 5,215 in year 3. Similarly, the number of marketable crops and food crops increase by 19 and 13, respectively.[16] This evidence suggests that the intervention is successful over the treatment

[15] In Table IAV of the Internet Appendix, we show that using the $\ln(1 + y)$ transformation of the count outcomes yields qualitatively similar results.

[16] The results are qualitatively similar when scaling the number of trees, marketable crops, and food crops by the size of the farm as reported in Table IAVI of the Internet Appendix.

period and likely the channel driving the increase in farmers' wealth.[17]

The estimated increase in the number of trees per farm may appear large at first glance, but it is consistent with the scale and design of the intervention. According to TREES' most recent impact report, the organization has planted approximately 420 million trees over its history, corresponding to about 40,219 hectares and 63,767 participating farms. This implies an average density of roughly 10,400 trees per hectare, or about 6,600 trees per farm. These figures closely align with our estimates and reflect the intensive, agroforestry-based nature of the intervention.

A. Pre-trends with EVI - Dynamic DID

The analysis thus far is limited by data availability, as we do not observe pre-treatment measures of household wealth, livestock ownership, or any of the other outcome variables beyond the baseline year in which the intervention begins. Although the results remain robust within household, the absence of pre-period observations raises the possibility that contemporaneous shocks or unobservable time-varying confounders may influence the findings. An analysis incorporating pre-trends would therefore provide additional credibility to the results presented above.

To address this concern, we turn to satellite-based measures of vegetation and, specifically, to the Enhanced Vegetation Index (EVI) to study the impact of the natural capital intervention on treated farms. While EVI is not a direct measure of household wealth, it offers several advantages in this context. First, farming constitutes the primary source of income for these households, and

[17]TREES also collects data on the number of trees, food crops and marketable crops for a larger sample of farms at different time intervals. However, this dataset has a few limitations: (i) it only includes the farm id, its location, and the three variables aforementioned and (ii) it has sparse data for year 3 of the treatment. Because farm fixed effects absorb all time-invariant heterogeneity and calendar-year fixed effects remove all aggregate shocks common to farms in a given year, the coefficients on the event-time indicators are identified exclusively from within–calendar-year variation across farms. In this panel, all farms observed in the calendar year corresponding to relative event time 3 are already treated and share the same event-time status. As a result, the indicator for relative year 3 is perfectly collinear with the calendar-year fixed effect and is mechanically dropped by the estimator. This lack of within-year cross-sectional variation implies that the effect in event year 3 is not identifiable in specifications with calendar-year and farm fixed effects. For this reason, when using this panel data, we exclude the calendar-year fixed effects or alternatively estimate a specification that aggregates all post-treatment periods into a single "post" indicator, which remains identifiable in the presence of year (or country-year) and farm fixed effects. The results reported in Table IAVIII of the Internet Appendix are robust and show a statistically and economically significant increase in all three outcome variables.

EVI captures differences in vegetation density, plant health, and biomass that are directly related to agricultural productivity. Higher EVI values typically reflect denser, healthier vegetation, whereas lower values indicate stressed or sparse plant cover, conditions that are strongly correlated with lower yields.[18]

We construct annual farm-level measures of median EVI for all farms for which TREES has collected at least the farms' coordinates and treatment year.[19] We focus on the median as it is less prone to being affected by pixels with extreme values and report robustness tests using the mean. We also compute the EVI measures for two sets of control farms: (1) farms that enrolled in the program but did not ultimately participate due to not meeting at least one of TREES' eligibility criteria, and (2) randomly selected non-participant farms. The second control group is constructed as follows. For each treated farm, we select a random point that is: (1) at least 1 km away from the treated farm, (2) at least 170 m away from any other treated farm (three times the radius of a 1-hectare circle), (3) within 50 km of the treated farm, and (4) located in an area classified as cropland, grassland, or shrubland by the ESA WorldCover product.[20]

Using these data, we estimate the following dynamic DiD model:

$$
\begin{aligned}
y_{i,c,t} = &\sum_{\substack{\ell=-3 \\ \ell\neq-1}}^{\ell=+5} \gamma_\ell 1(Year=\ell)^{\ell}_{i,c,t} + \sum_{\substack{\ell=-3 \\ \ell\neq-1}}^{\ell=+5} \lambda_\ell 1(Year=\ell)^{\ell}_{c,t} \times Treat_{i,c} \\
&+ \tau_i + \rho_{c,t} + \varepsilon_{i,c,t}.
\end{aligned} \tag{3}
$$

The coefficients λ_ℓ provide event-study estimates of how EVI evolves for treated relative to control

[18]This analysis focuses on quantities rather than prices, as it is unlikely that treated farmers—who constitute a small share of the local agricultural market—affect equilibrium crop prices. Thus, vegetation-based proxies are sufficient to capture relative differences in on-farm productivity between treated and control groups.

[19]Because exact farm boundaries are unavailable, we calculate EVI using all Sentinel-2 pixels within a 1-hectare circle centered on the latitude and longitude of each farm.

[20]Smallholder cropland, grassland, and shrubland are difficult to distinguish in 10 m satellite products in African landscapes, due to spectral similarity and frequent transitions between land states. Restricting controls to cropland alone would likely exclude many viable agricultural locations. In addition, including grassland and shrubland allows the control pool to reflect both active and fallow stages of smallholder agriculture. Since the goal of the control group is to approximate counterfactual locations with similar biophysical potential to the treated farms, these three categories provide an appropriate and inclusive representation of arable land in the study region.

farms.[21]

A limitation of standard two-way fixed effects (TWFE) estimators in settings with staggered treatment timing is that they may deliver biased estimates when treatment effects are heterogeneous over time or across cohorts (De Chaisemartin and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021; Athey and Imbens, 2022; Borusyak, Jaravel, and Spiess, 2024). Specifically, these estimators may deliver biased estimates when treatment effects are heterogeneous over time or across cohorts. To address these issues, we implement the estimator of Sun and Abraham (2021), which constructs cohort-specific event-study effects using only appropriate, never-treated or not-yet-treated farms as controls. This approach yields unbiased and interpretable dynamic treatment effects under staggered adoption and provides a robust complement to our baseline specifications.

As reported in Figure 5, our results do not reject the parallel-trends assumption both when using the TWFE and the Sun and Abraham (2021) models. Specifically, the median EVI exhibits no differential pre-treatment trends between treated and control farms. Following treatment, we observe a pronounced increase in EVI beginning in year 2, consistent with the biological trajectory of the natural capital intervention (Figure 5 and Table IV).[22]

Overall, these results reinforce the main finding: the estimated effects of the intervention on household wealth are unlikely to be driven by pre-existing trends or unobserved systematic differences between treated and control farms. Moreover, the detectable increase in EVI demonstrates that the intervention generates measurable improvements in vegetation and biomass, consistent with enhanced carbon sequestration and afforestation outcomes.

B. Linking Natural Capital Increases to Wealth

The natural capital intervention may increase household wealth through multiple channels. Here, we further examine the link between changes in natural capital and changes in wealth by testing whether higher natural-capital intensity is associated with larger increases in livestock hold-

[21] The treatment indicator is omitted as it is absorbed by the household fixed effects.

[22] The results are qualitatively similar when using the mean EVI as reported in Figure IA1 and Table IAXI of the Internet Appendix.

ings. Specifically, we estimate the following specification:

$$\Delta Y_i = \alpha + \beta\, \Delta \textit{Natural Capital}_i + \gamma\, \Delta X_i + \varepsilon_i, \tag{4}$$

where ΔY_i denotes the change in livestock units per hectare for farm i.

Because this analysis exploits cross-sectional variation in changes across farms, we estimate the model in first differences. This approach removes time-invariant farm-level heterogeneity, making farm fixed effects unnecessary in this specification. The key explanatory variable, $\Delta \textit{Natural Capital}_i$, captures changes in natural-capital intensity. We operationalize natural-capital intensity using three alternative measures: changes in the number of trees per hectare, changes in the number of marketable crops per hectare, and changes in the number of food crops per hectare.

The results reported in Table V show a positive association between increases in natural-capital intensity and increases in livestock units per hectare. Due to the high correlation between changes in marketable and food crops (correlation coefficient of 0.88), we estimate separate specifications for each component rather than including all three measures simultaneously.[23] Although these regressions do not identify causal effects, the results are consistent with the proposed mechanism and support the interpretation that improvements in natural capital are closely linked to wealth accumulation.

It is also possible that diversification benefits from planting multiple crops and trees reduce the risk of crop failure and income volatility. This mechanism likely operates in addition to—rather than as an alternative to—the productivity channel, as the EVI results show a dramatic increase in vegetation biomass, which is plausibly correlated with higher total farm yields.

[23] Including marketable and food crops jointly yields unstable estimates due to multicollinearity.

VI. Valuing the Economic Impact

A. Valuing Household Wealth Effects

We provide a simple back-of-the-envelope calculation of the economic magnitude of the wealth effects of the intervention for the average farmer in our sample. The key intuition is that in settings where formal savings institutions are limited or absent, livestock functions as a primary store of value and is therefore an appropriate proxy for wealth accumulation. We assume that the increase in farm productivity induced by the intervention is partly allocated toward the purchase of livestock and additional consumption. Because our data capture only the change in livestock holdings—and not other forms of savings or consumption—our estimates likely represent a lower bound on the overall impact of the intervention on household wealth.

Let W_0 denote the baseline value of livestock wealth for a representative household. Let p_j denote the price of livestock type $j = 1, \ldots, J$, and let L_{jt} denote the number of animals of that type held by a representative household at time t. The baseline value of livestock wealth for a representative household, W_0, is hence

$$W_0 = \sum_{j=1}^{J} p_j L_{j0}.$$

In each year, the number of animals increases by the effect estimated in Table II column (4). For instance,

$$L_{j1} = L_{j0} + \hat{\gamma}_1$$

We conservatively assume that each animal produces an annual cash flow of 10% of its asset value which we utilize to compute the annual incremental cash flow for each year of the treatment up to year 3. Then, we utilize the estimated cash flow in year 3 to compute the perpetuity value of the increased herd using the standard perpetuity formula.

$$Perpetuity_3 = \frac{W_3 \times 10\% \times (1+g)}{r-g},$$

where g represents the growth rate of the cash flow after year 3 and r represents the discount rate.[24] We then discount all cash flows, including the costs of the intervention, and compute the net present value (NPV) and internal rate of return (IRR) of the investment.

Using the estimated effects of the intervention on livestock ownership and valuing the resulting cash flows from increased herd size at local market prices, we estimate that the present value of livestock wealth gains—discounted back three years—exceeds the present value of program costs under conservative assumptions.[25] Specifically, the estimated NPV for the average farmer is $1,450 when using a discount rate of $r = 14.34\%$, corresponding to an internal rate of return (IRR) of 64.06%. This gain is equivalent to approximately 68% of Kenya's GDP per capita.[26].

Additional private wealth gains could be achieved by selling carbon offsets. To estimate this effect from carbon markets, we proceed as follows. First, we assume an average CO_2 sequestration rate of 20 kg (0.02 tonnes) per tree per year. Second, we estimate the number of trees planted per farmer using the average of the two Year 3 coefficients reported in Table III, columns (1) and (2), yielding 5,121 trees per farm. We assume that farmers replace dead trees so that the stock of trees remains constant over time, and we adopt a finite carbon-crediting horizon of 10 years.

For the carbon price, we use the average offset price for projects categorized as agroforestry, afforestation, reforestation, agricultural land management, or forest conservation reported by Allied Offsets ($7.70 per tonne).[27]

Because valuation is sensitive to discounting assumptions, we compute present values using a lower-bound rate equal to the social discount rate commonly applied in Social Cost of Carbon (SCC) calculations (2%) and a higher rate (8%) intended to reflect project-level risk, price uncertainty, and TREES' intermediation. Applying the standard finite annuity formula, the present value of

[24] We estimate r using the equity risk premium estimate of Kenya from Damodaran (2025) and g using Kenya's inflation rate from the World Bank for 2024 World Bank (2025).

[25] All parameters used in the calculation are reported in Table IAX in the Internet Appendix. We use conservative livestock price benchmarks from rural Kenya, based on guidance from TREES staff and validated using external sources.

[26] Kenya's GDP per capita in 2024 was $2,132. This information was collected from the World Bank Website (https://data.worldbank.org/indicator/NY.GDP.PCAP.CD?locations=KE)

[27] Results are qualitatively similar when restricting to agroforestry projects only. Carbon offset prices in countries where TREES operates vary substantially (ranging from $1 to $987, mean $5.72, median $8.00, standard deviation $12.33). After trimming the bottom and top 5$^{\text{th}}$ percentiles, the mean price is $7.70 and the median is $6.02.

carbon credit revenues for a farmer completing the TREES program today ranges from \$5,292 to \$7,084, equivalent to approximately 2.5–3.3 times Kenya's GDP per capita.[28]

B. Social Value of Carbon Sequestration

The environmental benefits are similarly substantial. TREES-supported plantings sequestered between 44 and 57 megatonnes (Mt) from 1989 to 2025 and are projected to sequester between 131 and 143 Mt of CO_2 for the next ten years—equivalent to avoiding approximately 1 trillion kilometers of travel by gasoline-powered vehicles, or about 30% of total vehicle kilometers driven in the United States in 2025.[29]

We also value the climate benefits of TREES' tree planting using a standard social cost of carbon (SCC) framework. Let P_τ denote the number of trees planted in year τ. We reconstruct annual planting cohorts using TREES' reported cumulative milestones (30 million trees by 2003, 100 million by 2015, and 420 million by 2025), interpolating annual plantings between milestones, and we project forward plantings from 2025 onward using an annual growth rate of 15% for ten years (i.e., the growth rate of tree planting between 2015 and 2025). For each cohort, we model survivorship using a constant annual survival probability $s = 0.926$ or $s = 0.9756$, consistent with a 50% or 80% ten-year survival rate. Each surviving tree is assumed to sequester $\phi = 0.02$ tons of CO_2 per year.

Annual expected CO_2 sequestration in year t is computed by summing contributions across all planting cohorts:

$$Q_t = \sum_{\tau \le t} P_\tau \, s^{\,t-\tau} \, \phi, \tag{5}$$

where Q_t is measured in tons of CO_2. We convert sequestration into a monetary climate benefit

[28] The valuation is computed as \$7.70 × 5,121 trees × 0.02 tCO_2 per year × $\frac{1-(1+r)^{-10}}{r}$, where r denotes the discount rate.

[29] Carbon sequestration estimates are based on an average CO_2 uptake of 20 kg (0.02 tonnes) per tree per year, an assumed survival rate of 50–80% over a ten-year horizon (corresponding to annual survival rates of 93.3–97.8%), and the number of trees planted by TREES. Survival rates vary widely depending on climate, landscape, and planting context. Emissions-equivalence calculations use UK government estimates of CO_2 emissions per kilometer driven by a petrol car (UK Government, Department for Energy Security and Net Zero, 2022) and aggregate vehicle miles traveled in the United States from FRED (Federal Reserve Bank of St. Louis, 2025).

using the SCC. Under a constant-SCC specification, annual benefits are given by

$$B_t = \mathrm{SCC} \times Q_t. \tag{6}$$

Under a time-varying SCC specification, we allow the SCC to grow at a constant real rate g:

$$\mathrm{SCC}_t = \mathrm{SCC}_{t_0}(1+g)^{t-t_0}, \qquad B_t = \mathrm{SCC}_t \times Q_t, \tag{7}$$

where t_0 denotes the base year.

We compute the present value (PV) of climate benefits by discounting annual benefits back to t_0 at real rate r:

$$\mathrm{PV} = \sum_{t=t_{\min}}^{t_{\max}} \frac{B_t}{(1+r)^{t-t_0}}. \tag{8}$$

In our baseline implementation, we set $t_{\max} = 2035$ to have more conservative estimates. The present value of climate benefits totals between \$38 and \$98 billion depending on the survival rate.

Overall, the combined economic and ecological magnitudes suggest that nature-positive agricultural interventions can generate returns that far exceed their costs, delivering simultaneous gains in rural livelihoods and ecosystem recovery. Agroforestry systems also enhance biodiversity, with early field evidence indicating increases in bird and insect activity on participating farms. Importantly, these economic magnitude estimates do not account for improvements in household health—discussed in the following section—or other potential positive spillovers. As a result, the estimated net benefits are likely a lower bound.

VII. Additional Effects

A. Health

The benefits of the natural capital intervention extend beyond financial and environmental outcomes. One of the organization's central objectives is to improve household health by enhancing food security and dietary diversity. We evaluate these impacts using several standard measures of food insecurity derived from the Household Food Insecurity Access Scale (HFIAS). The HFIAS was developed as part of the United States Agency for International Development's (USAID) Food and Nutrition Technical Assistance (FANTA) project to provide methodologically rigorous indicators of household food insecurity.[30]

We focus on three outcomes: (i) an indicator for lack of food, equal to one if the household reported having no food of any kind at least once in the past four weeks; (ii) an indicator for severe food insecurity, equal to one if the household is classified as severely food insecure according to the HFIAS; and (iii) a continuous measure of dietary diversity ("Food Diversity"), which ranges from 0 to 12, with higher values indicating more diverse diets.

The regression specifications are identical to eq. (2), except that health-related outcomes replace livestock ownership as the dependent variables. We find evidence that the intervention improves household health outcomes. Specifically, the results reported in Table VI show economically and statistically significant reductions in both the incidence of food scarcity and severe food insecurity, ranging between 92 and 135%. In addition, we find a statistically and economically significant increase in dietary diversity, suggesting that improvements in health outcomes are at least partly driven by more varied diets.

The results are robust to alternative specifications that exclude farm fixed effects and include pre-treatment household characteristics and county- or province-level fixed effects (Table IAIX).[31] Taken together, these findings suggest that increases in natural capital improve household health, which may in turn contribute to the observed gains in household wealth.

B. Direct Measures of Income

Due to data limitations, we are unable to run empirical tests similar to the baseline approach with direct income measures. As a complementary analysis, we estimate the effect of intervention on income by utilizing the dataset with direct income measures. Specifically, we match 28 control farms (those that enrolled in the program but did not start) to two treated farms (those in year

[30] The HFIAS is widely used by national and international agencies and non-profit organizations, including the Food and Agriculture Organization (FAO) and USAID.

[31] The household characteristics used as control variables are identical to those utilized in Table IAIV.

3 of the intervention). The matching is based on land size and household size using propensity scores. Although the sample is small, the results indicate that the total value produced (sold and consumed) by treated farmers is statistically significantly higher than that of control farmers as reported in Table VII. The results are robust to using alternative variables for the propensity score matching (Table IAXII). Naturally, these findings are limited by the very small number of observations, which constrains the strength of the conclusions. Nevertheless, the results are consistent with those obtained in the larger-sample analysis.

VIII. Additional Tests

As an additional robustness check, we re-estimate the baseline DiD model after excluding the largest and smallest farms, defined as those above the 95^{th} percentile and below the 5^{th} percentile of farm size, respectively. The results remain robust, as reported in Table IAXIII, columns (1)–(4), of the Internet Appendix. As a falsification test, we estimate the effect of the intervention on the number of household members—an outcome that the intervention is not expected to affect. Consistent with this expectation, the results reported in Table IAXIII, column (5), show no statistically significant effect.

We also conduct cross-sectional analyses to assess whether the intervention disproportionately benefits households with particular baseline characteristics. With the exception of an indicator for whether the household head is the most educated adult in the household, baseline household and local characteristics are not significantly associated with treatment effects. This pattern suggests that the intervention operates broadly across households with different socioeconomic profiles (Table IAXIV in the Internet Appendix). Taken together, these findings support the scalability of the intervention and suggest that its effectiveness is not confined to specific household types or local contexts.

IX. Conclusion

Our findings demonstrate that restoring natural capital through biodiversity-enhancing agricultural practices can yield substantial and sustained economic benefits for smallholder households. By leveraging a quasi-experimental intervention implemented by TREES for the Future, we provide causal evidence that investments in agroecological restoration—such as increasing tree cover, diversifying crops, and improving soil health—translate into higher wealth accumulation, improved food security, and measurable gains in on-farm natural capital detectable via satellite imagery. These results underscore that nature-positive interventions need not entail a trade-off between environmental conservation and economic development; rather, they can strengthen both rural livelihoods and ecosystem resilience.

In regions where agricultural productivity and household welfare are deeply intertwined with the condition of local ecosystems, our evidence highlights the potential for natural capital restoration to function as a scalable, cost-effective development strategy. More broadly, the study illustrates how collaborations with non-profit organizations, paired with high-resolution remote sensing and longitudinal microdata, can generate rigorous insights into the economic value of nature in data-poor settings. As global pressures on ecosystems intensify, policies and investments that integrate natural capital restoration into the core of rural development strategies may offer a promising pathway to simultaneously promote environmental sustainability and economic well-being.

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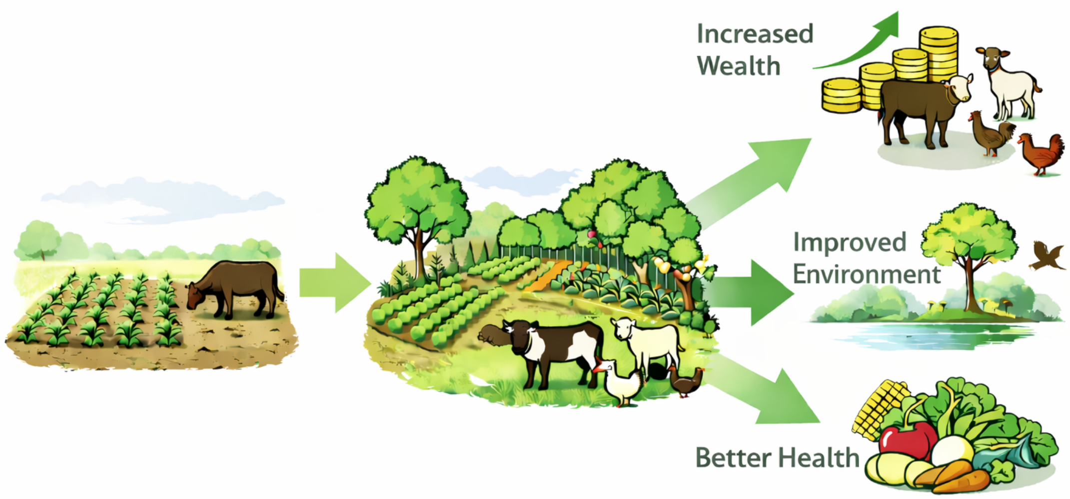
Figure 1
Natural Capital Intervention and Potential Outcomes



This figure summarizes the natural capital intervention by TREES and its potential outcomes.

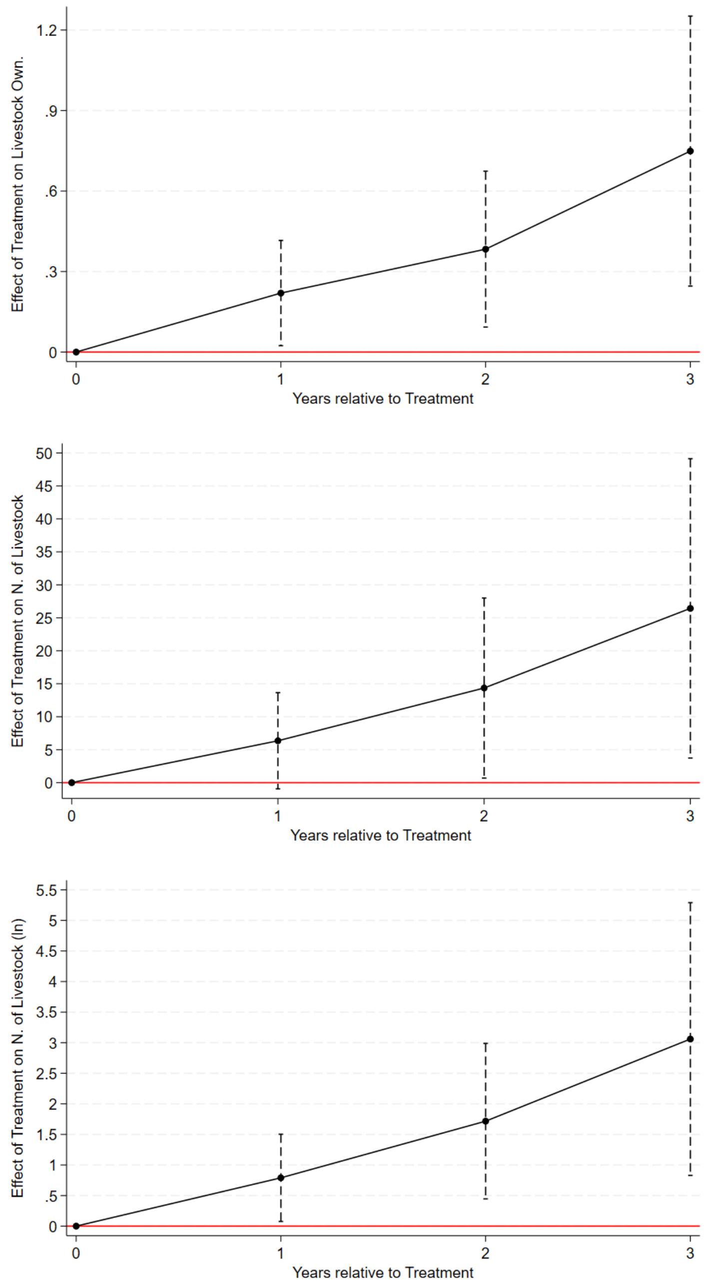
Figure 2

TREES Farms' location

This figure reports the location of farms that participated in the TREES program with at least latitude, longitude, and number of trees available.

Figure 3

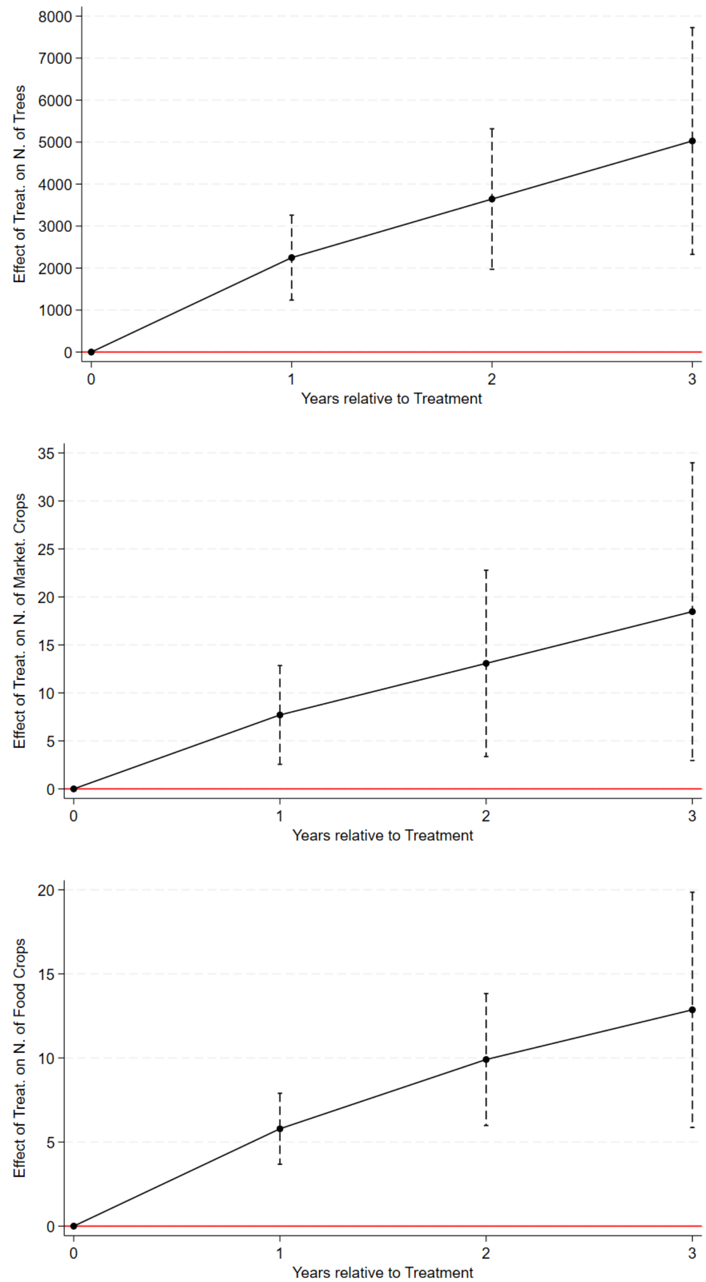
Natural Capital Intervention and Household Wealth



These figures report the DiD estimates of the effect of natural capital intervention on the households' likelihood to own livestock and the number of livestock animals. The regression model is described in eq. (2). The reference year is Year 0. The dots represent the coefficients on the year indicators post-treatment. The horizontal lines represent 90% confidence bands based on standard errors clustered by project area.

Figure 4

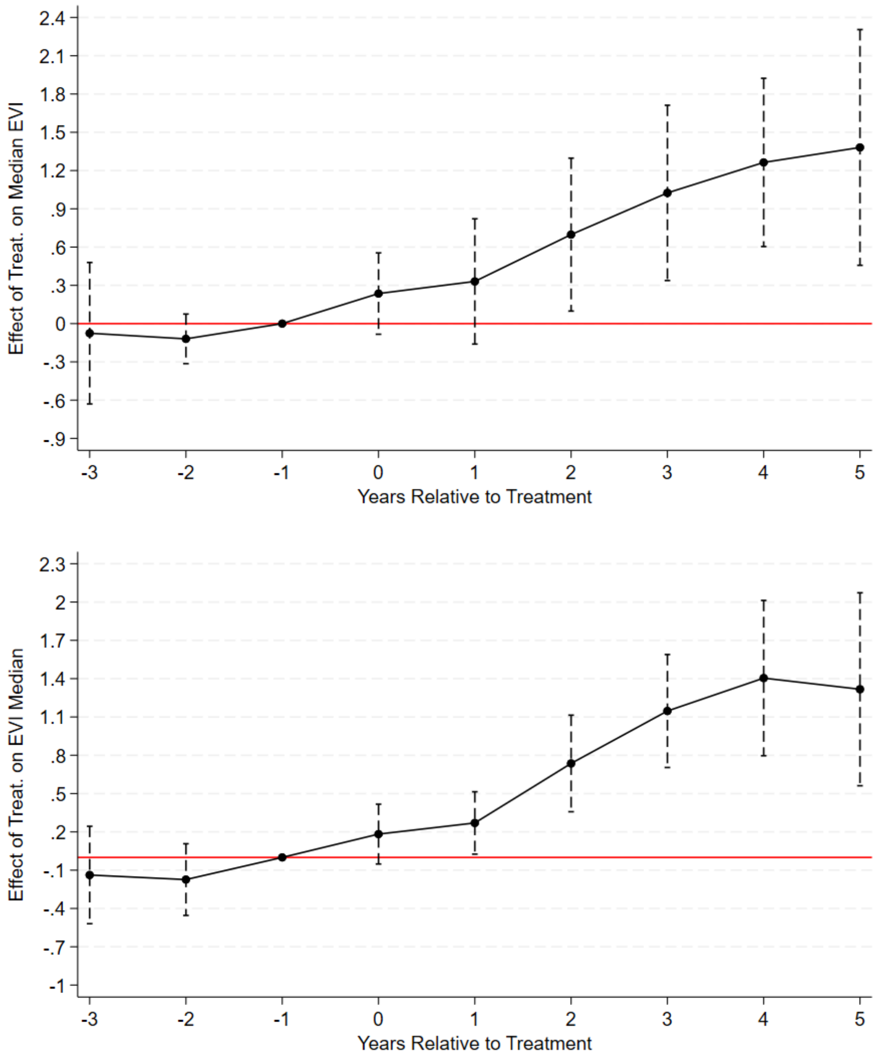
Natural Capital Intervention, Number of Trees, and Crops



These figures report the DiD estimates of the effect of the natural capital intervention on the households' number of trees, marketable crops, and food crops. The regression model is described in eq. (2). The reference year is Year 0. The dots represent the coefficients on the year indicators post-treatment. The horizontal lines represent 90% confidence bands based on standard errors clustered by project area.

Figure 5

Natural Capital Intervention and Median EVI



These figures report the DiD estimates of the effect of the natural capital intervention on the farms' median Enhanced Vegetation Index (EVI). The regression model is described in eq. (3). Panel A reports the results using the TWFE model. Panel B reports the results using the Sun and Abraham (2021) estimator. The reference year is $t-1$. The dots represent the coefficients on the year indicators post-treatment. The horizontal lines represent 90% confidence bands based on standard errors clustered by project area.

Table I: Summary Statistics

	Mean	Std. Dev.	Obs.	Min.	Max.
1(Own Livestock)	0.83	0.37	6,192	0.00	1.00
N. Livestock	12.07	12.63	6,192	0.00	114.00
N. Trees	746.25	905.92	6,187	0.00	4500.00
N. Marketable Products	5.75	5.05	6,191	0.00	25.00
N. Food Crops	5.42	4.40	6,191	0.00	21.00
1(No Food)	0.24	0.42	6,178	0.00	1.00
1(Food Insecure)	0.31	0.46	6,192	0.00	1.00
Food Diversity	7.11	2.39	6,192	0.00	12.00
Size (ha)	0.56	1.30	6,187	0.00	75.00
Tot. Household Members	8.61	6.03	6,142	0.00	107.00
Δ in GCP per Capita (USD)	0.01	0.07	6,192	-0.23	0.30
EVI Median	26.59	11.49	355,440	11.01	54.38
EVI Mean	28.93	11.13	355,440	1.67	71.48

This table reports the summary statistics for the variables used in the study.

Table II

Effect of the Intervention on Livestock Ownership on the Extensive and Intensive Margins.

Dependent Variable:	1(Own Livestock)		N. Livestock		N. Livestock (ln)	
	(1)	(2)	(3)	(4)	(5)	(6)
1(Year 1)	0.222**	0.220**	5.799	6.353*	0.768*	0.790**
	(2.12)	(2.13)	(1.52)	(1.71)	(1.98)	(2.17)
1(Year 2)	0.367*	0.383*	13.067*	14.355**	1.569**	1.715**
	(1.79)	(1.88)	(1.85)	(2.06)	(2.28)	(2.64)
1(Year 3)	0.732**	0.749**	24.709**	26.433**	2.816**	3.058***
	(2.08)	(2.10)	(2.11)	(2.28)	(2.39)	(2.69)
Controls	Y	Y	Y	Y	Y	Y
Farm FE	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	N	Y	N	Y	N
Country-Month FE	Y	N	Y	N	Y	N
Country-Year-Month FE	N	Y	N	Y	N	Y
Observations	1,206	1,195	1,206	1,195	1,206	1,195
R^2	0.647	0.653	0.671	0.677	0.666	0.671

This table reports estimates of the DiD regression (eq. (2)) of the effect of the natural capital intervention on an indicator equal to one if farm owns livestock, the number of livestock, and its natural log. The year indicators are equal to one for treated observations only as the control group is only available in year 0, the reference year. The control variable includes $0.25° \times 0.25°$ grid cell estimates of the change in gross local product from Rossi-Hansberg and Zhang (2025). The standard errors are clustered at the project area level. t-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table III

Effect of the Intervention on the Number of Trees and Crops.

Dependent Variable:	N. Trees		N. Mkt. Crops		N. Food Crops	
	(1)	(2)	(3)	(4)	(5)	(6)
1(Year 1)	2,205.4***	2,248.5***	7.627***	7.704***	5.691***	5.789***
	(4.20)	(4.36)	(2.86)	(2.94)	(4.63)	(5.37)
1(Year 2)	3,737.5***	3,643.3***	13.700***	13.075**	10.523***	9.909***
	(4.42)	(4.27)	(2.76)	(2.64)	(4.87)	(4.95)
1(Year 3)	5,215.0***	5,026.4***	19.524**	18.468**	14.062***	12.862***
	(3.79)	(3.65)	(2.48)	(2.33)	(3.80)	(3.60)
Controls	Y	Y	Y	Y	Y	Y
Farm FE	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	N	Y	N	Y	N
Country-Month FE	Y	N	Y	N	Y	N
Country-Year-Month FE	N	Y	N	Y	N	Y
Observations	1,206	1,195	1,206	1,195	1,206	1,195
R^2	0.856	0.864	0.798	0.804	0.842	0.846

This table reports estimates of the DiD regression (eq. (2)) of the effect of the natural capital intervention on the number of trees (columns (1)-(2)), marketable crops (columns (3)-(4)), and food crops (columns (5)-(6)). The year indicators are equal to one for treated observations only as the control group is only available in year 0, the reference year. The control variable includes $0.25° \times 0.25°$ grid cell estimates of the change in gross local product from Rossi-Hansberg and Zhang (2025). The standard errors are clustered at the project area level. t-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table IV
Effect of the Intervention on Median Enhanced Vegetation Index.

Dep. Var: Median EVI	(1)	(2)	(3)	(4)
Treat $\times$ 1(Year -3)	-0.076	-0.075	-0.208	-0.138
	(-0.27)	(-0.27)	(-1.07)	(-0.71)
Treat $\times$ 1(Year -2)	-0.123	-0.119	-0.183	-0.174
	(-1.23)	(-1.21)	(-1.22)	(-1.21)
Treat $\times$ 1(Year 0)	0.235	0.236	0.215*	0.183
	(1.45)	(1.45)	(1.74)	(1.53)
Treat $\times$ 1(Year 1)	0.330	0.331	0.302**	0.270**
	(1.32)	(1.32)	(2.45)	(2.17)
Treat $\times$ 1(Year 2)	0.698**	0.698**	0.744***	0.736***
	(2.27)	(2.28)	(3.86)	(3.82)
Treat $\times$ 1(Year 3)	1.027***	1.025***	1.129***	1.147***
	(2.90)	(2.92)	(4.96)	(5.08)
Treat $\times$ 1(Year 4)	1.266***	1.264***	1.392***	1.404***
	(3.73)	(3.76)	(4.35)	(4.53)
Treat $\times$ 1(Year 5)	1.384***	1.381***	1.356***	1.317***
	(2.91)	(2.93)	(3.55)	(3.42)
Model	TWFE		Sun and Abraham (2021)	
Controls	N	Y	N	Y
Farm FE	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y
Observations	355,440	355,387	355,440	355,387
R^2	0.931	0.931	0.932	0.932

This table reports estimates of the DiD regression (eq. (3)) of the effect of the natural capital intervention on the median EVI. Columns (1)-(2) report the results using the TWFE model and columns (3)-(4) report the results using the Sun and Abraham (2021) estimator. The control variable includes 0.25° $\times$ 0.25° grid cell estimates of change in gross local product from Rossi-Hansberg and Zhang (2025). The standard errors are clustered at the project area level. t-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table V
Relation between Natural Capital Intensity and Livestock Units.

Dep. Var.: Δ N. Livestock	(1)	(2)	(3)	(4)	(5)
Δ Trees per ha (1000s/ha)	3.447***			2.016**	1.938*
	(2.80)			(2.07)	(1.89)
Δ Market Crops per ha		0.522***			0.389***
		(5.20)			(3.89)
Δ Food Crops per ha			0.613***	0.450***	
			(4.58)	(3.98)	
Controls	Y	Y	Y	Y	Y
Country-Year F.E.	Y	Y	Y	Y	Y
Country-Month F.E.	Y	Y	Y	Y	Y
Observations	636	636	636	636	636
R^2	0.169	0.180	0.178	0.187	0.188

This table reports estimates of the first-difference regressions (eq. (4)) with the difference in number of livestock units as the dependent variable and the difference in natural capital intensity measures as the independent variables of interest. Δ Trees per ha represents the change in number of trees (in thousands) per hectare. Δ Market Crops per ha represents the number of marketable crops per hectare. Δ Food Crops per ha represents the number of food crops per hectare. The control variable includes $0.25° \times 0.25°$ grid cell estimates of change in gross local product from Rossi-Hansberg and Zhang (2025). The standard errors are clustered at the project area level. t-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table VI

Effect of the Intervention on Health-related Outcomes.

Dependent Variable:	No Food		Food Insecurity		Food Diversity	
	(1)	(2)	(3)	(4)	(5)	(6)
1(Year 1)	-0.436*	-0.416	-0.408**	-0.400*	1.405	1.378
	(-1.96)	(-1.72)	(-2.53)	(-1.98)	(1.66)	(1.55)
1(Year 2)	-0.826**	-0.744*	-0.727*	-0.647*	1.990	2.250*
	(-2.14)	(-1.74)	(-2.02)	(-1.98)	(1.48)	(1.89)
1(Year 3)	-1.350**	-1.215*	-1.024*	-0.920*	4.158*	4.581*
	(-2.13)	(-1.75)	(-1.85)	(-1.83)	(1.74)	(2.04)
Controls	Y	Y	Y	Y	Y	Y
Farm F.E.	Y	Y	Y	Y	Y	Y
Country-Year F.E.	Y	N	Y	N	Y	N
Country-Month F.E.	Y	N	Y	N	Y	N
Country-Year-Month F.E.	N	Y	N	Y	N	Y
Observations	1,201	1,190	1,206	1,195	1,206	1,195
R^2	0.722	0.737	0.695	0.716	0.719	0.723

This table reports estimates of the DiD regression (eq. (2)) of the effect of the natural capital intervention on various health-related outcome variables. No Food (columns (1)-(2)) is an indicator equal to one if in the past 4 weeks, there was ever no food to eat of any kind in the household. Food Insecurity (columns (3)-(4)) is an indicator equal to one if the household was categorized as severely food insecure according to the HFIAS and zero otherwise. Food Diversity (columns (5)-(6)) is an index ranging between 0 and 12 with 0 (12) being the lowest (highest) dietary diversity value. The year indicators are equal to one for treated observations only as the control group is only available in year 0, the reference year. The control variable includes 0.25° × 0.25° grid cell estimates of the change in gross local product from Rossi-Hansberg and Zhang (2025). The standard errors are clustered at the project area level. *t*-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table VII
Effect of the Intervention on Income from Crops

Dep. Var: Crop Value	Total	Consumed	Sold
	(1)	(2)	(3)
1(Post)	1.993***	1.991***	2.571***
	(4.34)	(4.58)	(3.54)
Propensity Score Match	Y	Y	Y
Observations	74	74	74
R^2	0.286	0.295	0.215

This table reports estimates of the DiD regression of the effect of the natural capital intervention on the natural log of the total crop value (column (1)), crop value consumed (column (2)), and crop value sold (column (3)). The post indicator is equal to one for treated observations only as the control group is only available in year 0, the reference year. The propensity score match is computed using the number of members of the household and the size of the farm. The sample includes two control observations for each treated one. Standard errors are robust to heteroskedasticity. *t*-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Internet Appendix for Restoring Nature, Creating Wealth: Evidence from Rural Households in Africa

I. Additional Details about the Natural Capital Intervention

TREES provides farmers with agroforestry seedlings, as well as fruit, nut, and timber trees. Agroforestry trees are multi-purpose fast-growing trees (MPFGs). These trees are generally provided in seed form as they are much easier to raise and quicker to grow in comparison to fruit and nut trees. Fruit trees are generally produced in central tree nurseries to ensure farmers receive high value grafted seedlings that will produce fruit in the future. There are still exceptions where fruit trees are given in seed form – the most common species being Papaya and passion fruit due to their ability to produce fruit within the first year of planting – sometimes as early as 6 months. Tree seeds are given in Year 1 ahead of the rainy season.[1]

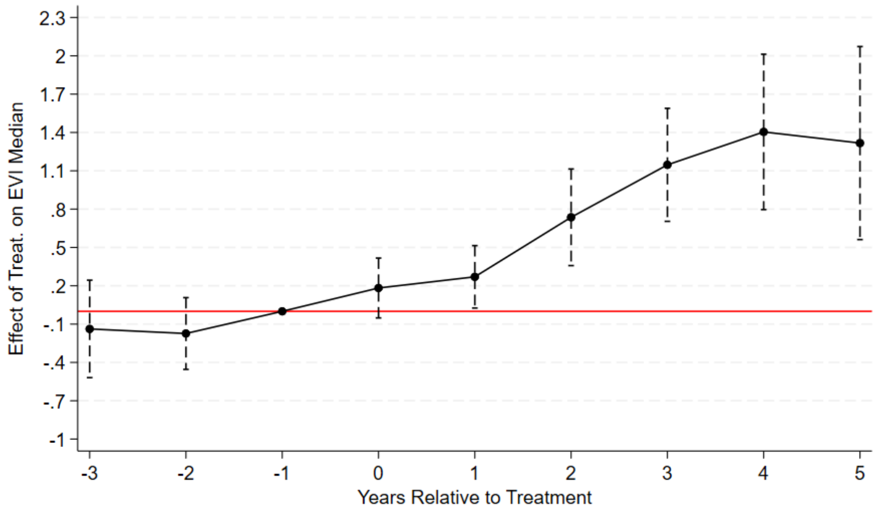
The types of seed given are as follows:

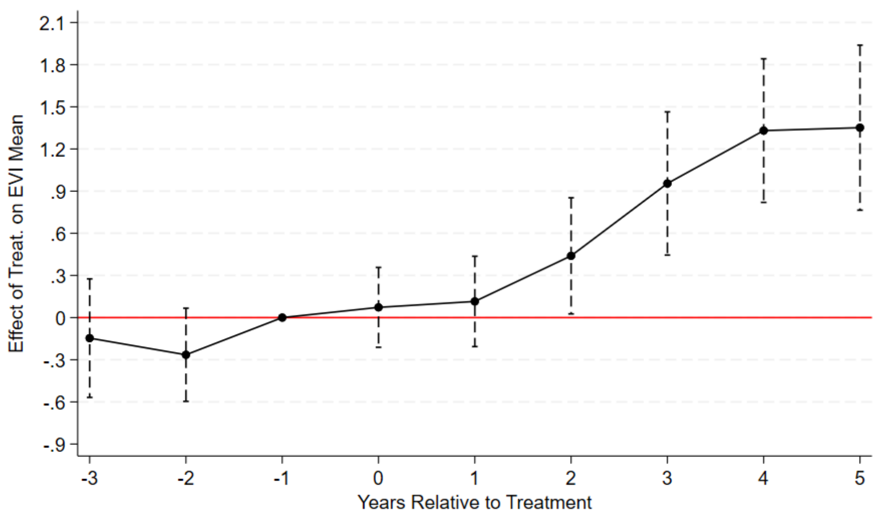
- Agroforestry or MPFG seeds: they will not produce fruit, but will provide farmers with secondary benefits including fuelwood, fodder, and green manure, which reduce farmer's external input needs and expenses, reduce demand on the farmer and families' time in gathering these natural resources, and reduce pressure on the surrounding land.
- Fruit tree seeds like papaya: fast growing fruit tree that will provide harvest within the first year of harvest. They provide important economic benefits early in program to keep farmers motivated in progressing through the approach.
- Fruit and nut tree seedlings like mango and cashew: these are the species that will take longer to bear fruit, usually after the end of project. TREES prioritizes the development and distribution of grafted fruit tree seedlings for an accelerated fruit production for farmers to obtain additional and significant economic gains during the life of the project. If these gains can be made within the 4-year project timeline, there is a higher chance farmers will have seen and experienced the benefits of the intervention and that they will continue the practices after the project ends.
- Timber tree seeds: These are the longest to produce their primary economic return and will not be ready for harvest until well after the project ends. Farmers can still obtain periodic benefits when pruning and thinning timber species.

[1] If a project is located where there are two rainy seasons, seeds will be given in preparation for each rainy season.

Figure IA1

Natural Capital Intervention and Mean EVI





These figures report the DiD estimates of the effect of the natural capital intervention on the farms' mean Enhanced Vegetation Index (EVI). The regression model is described in eq. (3). Panel A reports the results using the TWFE model. Panel B reports the results using the Sun and Abraham (2021) estimator. The reference year is $t-1$. The dots represent the coefficients on the year indicators post-treatment. The horizontal lines represent 90% confidence bands based on standard errors clustered by project area.

Table IAI
Variable Definitions.

Variable	Definition
Household Size	Total number of household members.
N. of Females in House.	Number of female household members.
Share of Females in House.	Fraction of household members who are female.
N. of Children	Total number of children aged 18 or younger in the household.
N. of Children under 5	Number of children aged five years or younger in the household.
Share of Children under 5	Fraction of household members aged five years or younger.
Highest Education Level	Highest grade completed by the most educated household member. The education levels are 0, 1, 2, 3, which correspond to no education, primary, secondary, and higher than secondary, respectively.
1(Main Income from Farming)	Indicator equal to one if farming is reported as the household's primary income source.
Farm Size (Hectares)	Total cultivated land area measured in hectares.
N. of Trees	Total number of trees on the farm.
Trees per Hectare	Number of trees per hectare of cultivated land.
EVI	Enhanced Vegetation Index
1(Own. Livestock)	Indicator equal to one if the household is reported as owning any livestock.
N. of Livestock	Total number of livestock animals owned by the household.
Number of Crops	Total number of distinct crops cultivated on the farm.
N. of Marketable Products	Total number of marketable crops cultivated on the farm.
N. of Food Crops	Total number of crops cultivated on the farm and utilized for consumption.
1(No Food)	Indicator equal to one if the household reported having no food of any kind in the household during the past week (World Bank survey) or the past four weeks (TREES survey).
1(Food Insecure)	Indicator equal to one if the household was categorized as severely food insecure according to the Household Food Insecurity Access Scale (HFIAS).
Food Diversity	Index ranging between 0 and 12 with 0 (12) being the lowest (highest) dietary diversity value.
Gross County Product (GCP)	$0.25° \times 0.25°$ grid cell estimates of the change in gross local product from Rossi-Hansberg and Zhang (2025).

This table reports definitions for the variables utilized in the paper.

Table IAII
Items and Services Provided by TREES for the Intervention.

	Years			
	1	2	3	4
Agroforestry Seed	X	X	X	X
Fruit Tree Seed	X	X	X	X
Timber Seed	X	X	X	X
Vegetable Seed	X	X	X	X
Shovel	X			
Hoe or Rake as needed	X			
Watering Can	X			
Wheelbarrow	X			
Pruning Shears	X			
Trainings (includes training materials and refreshments)	5	4	4	2

This table reports the list of items received by the farmers during the four years of the intervention.

Table IAIII
Sample Comparison between TREES and World Bank surveys in Tanzania.

Variable	Mean (TREES)	Mean (WB)	Difference	t-stat	N (TREES)	N (WB)
House. Size	7.000	6.564	0.436	1.45	283	349
N. of Females in House.	3.657	3.223	0.434**	2.53	283	349
Share of Females in House.	0.530	0.500	0.030*	1.91	283	349
N. of Children	4.198	3.685	0.514**	2.19	247	349
N. of Children under 5	1.615	1.189	0.426***	3.60	247	349
Share of Children under 5	0.237	0.168	0.068***	3.82	247	349
Highest Education Level	1.452	1.123	0.329***	6.39	283	349
Main Income from Farming	0.993	0.662	0.331***	12.81	283	349
Farm Size (Hectares)	0.729	3.008	-2.279***	-6.29	283	236
Number of Trees	62.731	241.839	-179.107**	-2.33	283	161
Trees per Hectare	143.446	106.314	37.133	0.85	281	137
N. of Livestock	4.230	55.606	-37.469***	-8.60	283	109
Livestock per Hectare	10.005	30.898	12.355*	1.85	281	95
N. of Crops	4.180	2.394	1.786***	7.53	283	297
1(Food Insecure)	0.484	0.000	0.484***	16.27	283	349
1(No Food)	0.385	0.014	0.371***	12.50	283	349

This table reports summary statistics for common variables present in both the survey collected by TREES and by the World Bank's (WB) Living Standards Measurement Study - Integrated Surveys on Agriculture in Tanzania. Variable definitions are provided in Table IAI.

Table IAIV

Effect of the Intervention on Livestock Ownership on the Extensive and Intensive Margins - Alternative Specifications.

Dependent Variable:	1(Own Livestock)		N. Livestock (ln)		N. Livestock per ha (ln)	
	(1)	(2)	(3)	(4)	(5)	(6)
1(Year 1)	0.110***	0.121***	0.435***	0.461***	1.005*	1.072**
	(3.56)	(3.47)	(5.06)	(4.75)	(1.88)	(2.22)
1(Year 2)	0.131***	0.139***	0.462***	0.478***	1.924**	1.992**
	(4.30)	(4.35)	(4.53)	(4.46)	(2.02)	(2.19)
1(Year 3)	0.245***	0.262***	0.848***	0.878***	3.559**	3.479**
	(5.33)	(5.63)	(5.26)	(5.26)	(2.21)	(2.20)
Controls	Y	Y	Y	Y	Y	Y
City/Province F.E.	Y	Y	Y	Y	N	N
Farm F.E.	N	N	N	N	Y	Y
Country-Year F.E.	Y	N	Y	N	Y	N
Country-Month F.E.	Y	N	Y	N	Y	N
Country-Year-Month F.E.	N	Y	N	Y	N	Y
Observations	5,567	5,563	5,567	5,563	1,206	1,167
R^2	0.287	0.292	0.277	0.282	0.660	0.674

This table reports estimates of the DiD regression (eq. (2)) of the effect of the natural capital intervention on an indicator equal to one if the farm owns livestock, the number of livestock (ln), and the number of livestock per hectare (ln). The year indicators are equal to one for treated observations only as the control group is only available in year 0, the reference year. The control variable includes $0.25° \times 0.25°$ grid cell estimates of the change in gross local product from Rossi-Hansberg and Zhang (2025) as well as pre-treatment household characteristics. The household characteristics include indicators for whether the household head is the most educated member or female as well as the age of the head of the household, the number of household members, and the size of the farm. The standard errors are clustered at the project area level. *t*-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table IAV

Effect of the Intervention on the Natural log of Number of Trees and Crops.

Dependent Variable:	N. Trees (ln)		N. Mkt. Crops (ln)		N. Food Crops (ln)	
	(1)	(2)	(3)	(4)	(5)	(6)
1(Year 1)	5.702***	5.805***	1.189***	1.219***	0.762***	0.783***
	(9.02)	(8.95)	(3.19)	(3.44)	(3.80)	(4.40)
1(Year 2)	8.211***	8.317***	1.953***	1.892***	1.375***	1.296***
	(6.45)	(6.46)	(2.87)	(2.91)	(4.10)	(4.32)
1(Year 3)	9.882***	9.989***	2.649**	2.553**	1.702***	1.558***
	(4.83)	(4.78)	(2.36)	(2.35)	(2.78)	(2.67)
Controls	Y	Y	Y	Y	Y	Y
Farm F.E.	Y	Y	Y	Y	Y	Y
Country-Year F.E.	Y	N	Y	N	Y	N
Country-Month F.E.	Y	N	Y	N	Y	N
Country-Year-Month F.E.	N	Y	N	Y	N	Y
Observations	1,206	1,195	1,206	1,195	1,206	1,195
R^2	0.906	0.909	0.797	0.802	0.817	0.822

This table reports estimates of the DiD regression (eq. (2)) of the effect of the natural capital intervention on the natural log of the number of trees (columns (1)-(2)), marketable crops (columns (3)-(4)), and food crops (columns (5)-(6)). The year indicators are equal to one for treated observations only as the control group is only available in year 0, the reference year. The control variable includes $0.25° \times 0.25°$ grid cell estimates of the change in gross local product from Rossi-Hansberg and Zhang (2025). The standard errors are clustered at the project area level. t-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table IAVI
Effect of the Intervention on the Natural log of Number of Trees and Crops Scaled by Farm Size.

Dependent Variables (ln):	Trees/ha		Mkt. Crops/ha		Food Crops/ha	
	(1)	(2)	(3)	(4)	(5)	(6)
1(Year 1)	5.983***	6.069***	1.467***	1.519***	0.827***	0.867***
	(8.88)	(8.97)	(3.46)	(3.71)	(3.54)	(3.97)
1(Year 2)	8.533***	8.694***	2.236***	2.256***	1.257***	1.216***
	(6.33)	(6.59)	(2.76)	(2.91)	(3.24)	(3.52)
1(Year 3)	10.355***	10.512***	3.110**	3.122**	1.527**	1.417*
	(4.83)	(4.94)	(2.29)	(2.35)	(2.06)	(1.95)
Controls	Y	Y	Y	Y	Y	Y
Farm F.E.	Y	Y	Y	Y	Y	Y
Country-Year F.E.	Y	N	Y	N	Y	N
Country-Month F.E.	Y	N	Y	N	Y	N
Country-Year-Month F.E.	N	Y	N	Y	N	Y
Observations	1,206	1,195	1,206	1,195	1,206	1,195
R^2	0.898	0.901	0.793	0.797	0.817	0.821

This table reports estimates of the DiD regression (eq. (2)) of the effect of the natural capital intervention on the natural log of the number of trees (column (1)-(2)), marketable crops (column (3)-(4)), and food crops (column (5)-(6)) scaled by the size of the farm. The year indicators are equal to one for treated observations only as the control group is only available in year 0, the reference year. The control variable includes 0.25° × 0.25° grid cell estimates of the change in gross local product from Rossi-Hansberg and Zhang (2025). The standard errors are clustered at the project area level. *t*-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table IAVII

Effect of the Intervention on the Number of Trees and Crops - Alternative Fixed Effects.

Dependent Variable:	N. Trees		N. Mkt. Crops		N. Food Crops	
	(1)	(2)	(3)	(4)	(5)	(6)
1(Year 1)	1,193.5***	1,272.4***	4.134***	4.685***	4.133***	4.574***
	(7.79)	(7.86)	(4.18)	(4.71)	(5.43)	(6.04)
1(Year 2)	1,526.9***	1,592.3***	5.553***	5.895***	6.019***	6.336***
	(6.69)	(7.10)	(6.80)	(7.12)	(5.96)	(6.57)
1(Year 3)	2,043.6***	2,128.7***	7.411***	7.732***	7.760***	8.122***
	(4.82)	(5.15)	(6.14)	(6.14)	(4.68)	(5.13)
Controls	Y	Y	Y	Y	Y	Y
City/Province F.E.	Y	Y	Y	Y	Y	Y
Country-Year F.E.	Y	N	Y	N	Y	N
Country-Month F.E.	Y	N	Y	N	Y	N
Country-Year-Month F.E.	N	Y	N	Y	N	Y
Observations	5,671	5,667	5,671	5,667	5,671	5,667
R^2	0.484	0.495	0.464	0.474	0.502	0.513

This table reports estimates of the DiD regression (eq. (2)) of the effect of the natural capital intervention on the number of trees (columns (1)-(2)), marketable crops (columns (3)-(4)), and food crops (columns (5)-(6)), The year indicators are equal to one for treated observations only as the control group is only available in year 0, the reference year. The control variable includes $0.25° \times 0.25°$ grid cell estimates of the change in gross local product from Rossi-Hansberg and Zhang (2025). The standard errors are clustered at the project area level. t-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table IAVIII

Effect of the Intervention on the Number of Trees and Crops - Full Sample.

Dependent Variable:	N. Trees		N. Mkt. Crops		N. Food Crops	
	(1)	(2)	(3)	(4)	(5)	(6)
1(Year 1)	915.4***		4.159***		3.046***	
	(12.22)		(9.80)		(87.24)	
1(Year 2)	1,456.0***		7.190***		5.402***	
	(15.68)		(14.05)		(146.57)	
1(Year 3)	1,584.3***		8.852***		6.230***	
	(14.07)		(12.87)		(142.13)	
1(Post)		627.9***		1.848***		1.626***
		(5.75)		(3.55)		(4.10)
Controls	Y	Y	Y	Y	Y	Y
Farm F.E.	Y	Y	Y	Y	Y	Y
Country F.E.	Y	N	Y	N	Y	N
Country-Year F.E.	N	Y	N	Y	N	Y
Observations	67,402	67,398	67,831	67,827	67,831	67,827
R^2	0.628	0.655	0.652	0.707	0.646	0.693

This table reports estimates of the DiD regression (eq. (2)) of the effect of the natural capital intervention on the number of trees (columns (1)-(2)), marketable crops (column (3)-(4)), and food crops (column (5)-(6)). The year indicators are equal to one for treated observations only as the control group is only available in year 0, the reference year. The post indicator is equal to one for treated observations in years 1 to 3. The control variable includes $0.25° \times 0.25°$ grid cell estimates of the change in gross local product from Rossi-Hansberg and Zhang (2025). The standard errors are clustered at the project area level. t-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table IAIX

Effect of the Intervention on Health-related Outcomes - Alternative Specifications.

Dependent Variable:	No Food		Food Insecurity		Food Diversity	
	(1)	(2)	(3)	(4)	(5)	(6)
1(Year 1)	-0.101**	-0.073	-0.141***	-0.121**	0.526	0.520
	(-2.11)	(-1.42)	(-2.73)	(-2.22)	(1.58)	(1.41)
1(Year 2)	-0.161**	-0.140**	-0.197***	-0.178**	0.842**	0.837**
	(-2.54)	(-2.17)	(-2.66)	(-2.38)	(2.24)	(2.11)
1(Year 3)	-0.184**	-0.155*	-0.199**	-0.172**	1.650***	1.698***
	(-2.36)	(-1.98)	(-2.32)	(-2.02)	(3.02)	(3.02)
Controls	Y	Y	Y	Y	Y	Y
City/Province F.E.	Y	Y	Y	Y	Y	Y
Country-Year F.E.	Y	N	Y	N	Y	N
Country-Month F.E.	Y	N	Y	N	Y	N
Country-Year-Month F.E.	N	Y	N	Y	N	Y
Observations	5,662	5,658	5,671	5,667	5,671	5,667
R^2	0.270	0.277	0.257	0.263	0.333	0.336

This table reports estimates of the DiD regression (eq. (2)) of the effect of the natural capital intervention on various health-related outcome variables. No food (columns (1)-(2)) is an indicator equal to one if in the past 4 weeks, there was ever no food to eat of any kind in the household. Food Insecurity (columns (3)-(4)) is an indicator equal to one if the household was categorized as severely food insecure according to the HFIAS and zero otherwise. Food Diversity (columns (5)-(6)) is an index ranging between 0 and 12 with 0 (12) being the lowest (highest) dietary diversity value. The year indicators are equal to one for treated observations only as the control group is only available in year 0, the reference year. The control variable includes $0.25° \times 0.25°$ grid cell estimates of the change in gross local product from Rossi-Hansberg and Zhang (2025) as well as pre-treatment household characteristics. The household characteristics include indicators for whether the household head is the most educated member or female as well as the age of the head of the household, the number of household members, and the size of the farm. The standard errors are clustered at the project area level. *t*-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table IAX
Wealth Increase Calculation Parameters.

Variable	Estimate	Source
Baseline N. Livestock	12.07	TREES data
Baseline % Cows	16.40	TREES data
Baseline % Goats	16.24	TREES data
Baseline % Sheep	8.63	TREES data
Baseline % Chickens	54.94	TREES data
Baseline % Mule/Donkey	4.89	TREES data
Price of Cow	\$619	TREES Staff
Price of Goat	\$154	TREES Staff
Price of Sheep	\$46	TREES Staff
Price of Chicken	\$5	TREES Staff
Price of Mule/Donkey	\$116	TREES Staff
CF over Asset Value (%)	10	Estimate
r (%)	14.34	Damodaran (2025)
g (%)	4.5	World Bank (2025)

This table reports estimates of the parameters used in the valuation of the wealth effect of the natural capital intervention. The livestock price estimates are collected by TREES's taff from Kenya and are reported in USD.

Table IAXI

Effect of the Intervention on the Mean Enhanced Vegetation Index.

Dep. Var: Mean EVI	(1)	(2)	(3)	(4)
Treat × 1(Year −3)	0.041	0.042	-0.133	-0.146
	(0.11)	(0.11)	(-0.64)	(-0.68)
Treat × 1(Year −2)	-0.173	-0.172	-0.250	-0.265
	(-0.92)	(-0.92)	(-1.36)	(-1.56)
Treat × 1(Year 0)	0.126	0.125	0.073	0.073
	(0.90)	(0.89)	(0.50)	(0.50)
Treat × 1(Year 1)	0.207	0.206	0.136	0.115
	(0.86)	(0.85)	(0.84)	(0.70)
Treat × 1(Year 2)	0.329	0.329	0.429**	0.439**
	(0.91)	(0.91)	(2.02)	(2.08)
Treat × 1(Year 3)	0.802*	0.801*	0.939***	0.954***
	(1.95)	(1.97)	(3.57)	(3.67)
Treat × 1(Year 4)	1.136***	1.135***	1.314***	1.331***
	(3.22)	(3.24)	(4.85)	(5.10)
Treat × 1(Year 5)	1.232***	1.231***	1.411***	1.351***
	(3.08)	(3.11)	(4.64)	(4.51)
Model	TWFE		Sun and Abraham (2021)	
Controls	N	Y	N	Y
Farm FE	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y
Observations	355,440	355,387	355,440	355,387
R^2	0.723	0.723	0.723	0.723

This table reports estimates of the DiD regression (eq. (3)) of the effect of the natural capital intervention on the mean EVI. Columns (1)-(2) report the results using the TWFE model and columns (3)-(4) report the results using the Sun and Abraham (2021) estimator. The control variable includes 0.25° × 0.25° grid cell estimates of change in gross local product from Rossi-Hansberg and Zhang (2025). The standard errors are clustered at the project area level. *t*-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table IAXII

Effect of the Intervention on the Income from Crops - Alternative Matching Variables.

Dep. Var.: Crop Value	Total (1)	Consumed (2)	Sold (3)
1(Post)	2.093***	2.103***	2.682***
	(4.51)	(4.84)	(3.66)
Propensity Score Match	Y	Y	Y
Observations	74	74	74
R^2	0.286	0.295	0.215

This table reports estimates of the DiD regression (eq. (2)) of the effect of the natural capital intervention on the natural log of the total crop value (column (1)), crop value consumed (column (2)), and crop value sold (column (3)). The post indicator is equal to one for treated observations only as the control group is only available in year 0, the reference year. The propensity score match is computed using the number of members of the household, the size of the farm, and whether the farm owns livestock. The sample includes two control observations for each treated one. Standard errors are robust to heteroskedasticity. *t*-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table IAXIII

Effect of the Intervention on Livestock Ownership - Additional Robustness.

Dependent Variable:	1(Own Livestock)		N. Livestock (ln)		House. Members
	(1)	(2)	(3)	(4)	(5)
1(Year 1)	0.198*	0.240**	0.662*	0.842*	0.318
	(1.94)	(2.23)	(1.81)	(1.98)	(0.23)
1(Year 2)	0.376*	0.424*	1.661**	1.747**	-2.988
	(1.90)	(1.89)	(2.52)	(2.25)	(-1.15)
1(Year 3)	0.746**	0.813**	2.968**	3.134**	-2.430
	(2.07)	(2.08)	(2.49)	(2.37)	(-0.51)
Sample	Size $< 95^{th}$	Size $> 5^{th}$	Size $< 95^{th}$	Size $> 5^{th}$	Full
Controls	Y	Y	Y	Y	Y
Farm FE	Y	Y	Y	Y	Y
Country-Year-Month FE	Y	Y	Y	Y	Y
Observations	1,090	1,160	1,090	1,160	1,141
R^2	0.658	0.653	0.669	0.671	0.843

This table reports estimates of the DiD regression (eq. (2)) of the effect of the natural capital intervention on an indicator equal to one if the farm owns livestock, the number of livestock (ln), and the number of household members. The sample in columns (1) and (3) ((2) and (4)) excludes farms that are larger (smaller) than the 95^{th} (5^{th}) percentile of farms in the sample. The year indicators are equal to one for treated observations only as the control group is only available in year 0, the reference year. The control variable includes $0.25^\circ \times 0.25^\circ$ grid cell estimates of the change in gross local product from Rossi-Hansberg and Zhang (2025). The standard errors are clustered at the project area level. t-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table IAXIV

Relation between Baseline Household Characteristics and Livestock Units.

Dep. Var.: Δ N. Livestock	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
House. Head Age	-0.101									
	(-1.03)									
House. Head Gender		1.059								
		(0.57)								
1(Adult Most Edu.)			6.779***							
			(2.74)							
N. House. Members				-0.503						
				(-1.44)						
N. of Children to Tot.					-5.308					
					(-1.44)					
Females to Tot.						-0.075				
						(-0.93)				
1(Worried Food)							2.184			
							(0.94)			
1(Lacked Food)								1.637		
								(0.69)		
GCP per Capita									-2.349	
									(-0.91)	
Cell Population										0.000
										(0.34)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-Month F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	632	636	624	629	560	629	630	632	636	636
R^2	0.134	0.132	0.143	0.143	0.137	0.141	0.136	0.138	0.132	0.132

This table reports estimates of the first-difference regressions (eq. (4)) with the difference in the number of livestock units as the dependent variable and various household and local characteristics as the independent variables of interest. The control variable includes $0.25° \times 0.25°$ grid cell estimates of change in gross local product from Rossi-Hansberg and Zhang (2025). The standard errors are clustered at the project area level. t-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.