EXPLORING CROP YIELD DYNAMICS ACROSS SUB-SAHARAN AFRICA: A SIX COUNTRY STUDY.

by

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As members of the Master's Committee, we certify that we have read the thesis prepared by Rodrigo Jose Guerra Su, titled Exploring Crop Yield Dynamics Across Sub-Saharan Africa: A Six Country Study and recommend that it be accepted as fulfilling the dissertation requirement for the Master's Degree.

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I hereby certify that I have read this thesis prepared under my direction and recommend that it be accepted as fulfilling the Master's requirement.

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Thank you all for being part of this journey.

LAND ACKNOWLEDGMENT

We respectfully acknowledge the University of Arizona is on the land and territories of Indigenous peoples. Today, Arizona is home to 22 federally recognized tribes, with Tucson being home to the O'odham and the Yaqui. Committed to diversity and inclusion, the University strives to build sustainable relationships with sovereign Native Nations and Indigenous communities through education offerings, partnerships, and community service.

DEDICATION

Dedicado a toda mi familia, especialmente a mi mamá, mi papá, mi hermana, y mi hermano, quienes siempre me apoyaron y motivaron a pesar de la distancia. También para todos mis seres queridos, incluyendo aquellos que no están físicamente presentes, pero que siempre permanecen con nosotros en espíritu.

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ABSTRACT

Millions of people rely on agriculture for their livelihoods and it is the backbone of the economy in many developing countries. Improving agricultural yields is widely recognized as a key strategy for reducing poverty and ensuring food security around the globe. This paper examines agricultural productivity trends and the factors influencing them between 2008 and 2021 in six Sub-Saharan African countries. We estimate six models across different levels of aggregation (plot, household, manager, and cluster) to assess changes in productivity over time. Our findings show no evidence of yield growth or improvement, with agricultural productivity remaining unchanged across levels over time. Our results also suggest that while agricultural inputs are associated with higher yields, household characteristics and plot manager traits are linked to less favorable outcomes, which could help explain the lack of yield improvement. These findings contribute to ongoing discussions about which policy tools can best support smallholder farmers in Sub-Saharan Africa in increasing agricultural productivity.

Chapter 1

Introduction

Agriculture is the backbone of the economy in many developing countries, with millions of people securing their livelihoods in the sector. Boosting agricultural productivity is an essential component of reducing poverty levels and ensuring food security across the globe. As smallholder agriculture is the most common farming system in Sub-Saharan Africa (SSA) and plays a key role in household livelihoods (FAO, 2009; Larson et al., 2014; Nyarindo et al., 2024), many efforts and investments have focused on improving smallholder crop production. Advancements in knowledge and agricultural innovations have previously proven to increase food crop yields and per capita income in developing countries (Gollin et al., 2021). Understanding the factors affecting crop yields can help inform policy decisions aimed at improving productivity.

Agricultural technologies and innovations are expected to increase crop production and yields over time (Boserup, 1966), but in reality, agricultural productivity in developing countries is increasing at decreasing rates (Fuglie, 2018). This suggests a limit on the capacity for agricultural innovations and technologies to increase growth in the sector. Recent literature suggests that agricultural production in SSA remains low compared to other parts of the world due to various factors, including climate, soil quality, and the adoption of technology (Bjornlund et al., 2020; Fosso Djoumessi, 2022). This slow progress is also reflected in the large gap between agriculture and other sectors, where productivity remains substantially lower in farming even after accounting for differences in resources (Gollin et al., 2014; Gollin, 2023). Concerns about the lack of yield improvement are not new. Nearly two decades ago, World Bank (2007) observed little evidence of increased smallholder productivity; this was recently affirmed by Wollburg et al. (2024).

In this paper, we explore agricultural productivity trends in SSA. We find no evidence of improvement in agricultural productivity, regardless of the level of analysis. We see no growth in agricultural productivity at the plot-, household-, manager-, nor cluster-level.[1] Given this, we also explore the factors that contribute to these unchanging yields across models, finding that, while some factors support yield growth, others may help explain why agricultural productivity have not improved over time. These different contributions may cancel each other out, constraining improvements in productivity.

Our key finding is that there is no improvement in aggregate agricultural productivity from 2008 to 2021 across the six Sub-Saharan African countries examined in this study (Ethiopia, Malawi, Mali, Niger, Nigeria, and Tanzania). We identify a declining trend at the plot-level, controlling for plot- and household- characteristics, plot manager traits, and weather. When estimating plot-level productivity trends for each country, we find different patterns across them, although there is no evidence of yield improvement at the regional level when grouped together. At higher levels of aggregation, none of our specifications shows any change, and no specification demonstrates a positive and statistically significant growth trend in productivity over time. This raises important questions about the effectiveness of agricultural investments and highlights the need to understand the factors that constrain productivity growth.

To better understand agricultural productivity growth - or the lack thereof - we investigate the variables which may explain why yields have not improved in the region. We examine a set of variables representing plot, household, and plot manager characteristics. Our analysis shows that agricultural inputs, such as fertilizer, seed, and labor, have a positive and statistically significant effect across different aggregation levels. However, we find that certain household characteristics and plot manager traits are negatively associated with productivity. These opposing effects could help explain the lack of yield improvement over time. This finding is important given that many efforts to boost agricultural productivity in the region focus on promoting modern input adoption, often with limited consideration of household and plot manager characteristics that would be important for improved targeting and effectiveness of inputs.

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[1] Clusters are defined by GPS coordinates that are geo-referenced at the enumeration area (EA) level, with a randomly applied offset to protect household confidentiality: zero to two kilometers in urban areas and zero to five kilometers in rural areas.

To analyze agricultural productivity trends in SSA, we estimate six regression models using a cross-country panel dataset. These models are constructed at different levels, including plot-, household-, manager-, and cluster-level, to evaluate if yields are improving at any of these aggregations. Our baseline specification is a plot-level model that controls for agricultural inputs, household characteristics, plot manager traits, weather, and country fixed effects. We then adapt this framework to other levels by aggregating variables accordingly and applying household, plot manager, and cluster fixed effects. This approach allows us to examine whether productivity is improving for smallholders and leading to broader benefits in agricultural areas.

Changes in agricultural productivity are often attributed to changes in input use, particularly the adoption of improved seed varieties and the use of inorganic fertilizers (Gollin et al., 2021; Takahashi et al., 2020). The adoption of new technologies tends to have positive effects for farmers. However, in SSA, input use is limited by several factors. Farmers face challenges in adopting improved crop varieties due to limited access to local information or a preference for traditional varieties (Bezu et al., 2014; Khonje et al., 2015; Shiferaw et al., 2015). Similarly, the application of organic fertilizers is often limited by accessibility issues (Minten et al., 2013) and/or credit constraints (Holden and Lunduka, 2014; Lambrecht et al., 2014). As a result, many farmers continue to rely on traditional practices that constrain productivity growth and limit potential improvements in agricultural output.

Further, while increased input use is associated with a boost in agricultural productivity, evidence suggests that input use can have diminishing returns, leading to lower crop yields per additional unit applied (Spillman, 1923; Chavas et al., 2010). Although modern input use varies across SSA, farmers in the region tend to use insufficient improved agricultural inputs to increase crop productivity and do not always adjust input levels based on their operating environment (Sheahan and Barrett, 2017). Evidence suggests that adoption rates for modern agricultural input remain low in SSA countries (Liverpool-Tasie et al., 2017; Ricker-Gilbert, 2024), even when facing constraints like growing population density, climate change and weather variability, and limited irrigated land (Josephson et al., 2014; Ricker-Gilbert et al., 2014; Sheahan and Barrett, 2017; World Bank, 2013).

As modern input adoption remains low, farmers often turn to expanding agricultural land as a solution to increase productivity. Crop production growth in SSA is often driven by land extensification and extensive practices rather than intensification. Since the 2000s, about 75% of SSA's crop production growth has been explained by bringing more land into farming, while only 25% has resulted from improvements in crop yields (Jayne and Sanchez, 2021).

Agricultural productivity is also affected by traits of the farmer. Age, education, experience, and gender are all explored in the literature as explanations for productivity differences among farmers. Gender is of particular interest, as evidence suggests significant differences in productivity outcomes between female- and male-managed plots. Prior studies have found that women-managed plots are less productive than those managed by men, even when controlling for factors such as plot manager characteristics, crop type, and production inputs (Kilic et al., 2015; Slavchevska, 2015; Oseni et al., 2015; Aguilar et al., 2015). They attribute these gender disparities to differences in access to agricultural inputs, investment in land and technology, market opportunities, among other factors. As men exit agriculture and diversify into over livelihoods, women are increasingly left on farm, responsible for agricultural production (Kawarazuka et al., 2022; Leder, 2022; Najjar, 2021; Slavchevska et al., 2019). This may have consequences on overall agricultural productivity, if women increasingly are responsible for food production across SSA.

Understanding the drivers behind unchanging yields is critical for designing effective policies that enhance rural livelihoods and food security in SSA. While considerable attention has been placed on promoting modern input use, our findings suggest that this alone may be insufficient. Household and plot manager characteristics can reduce the positive impact of using modern inputs, showing that policies need to address more than just input access. Programs should also focus on addressing challenges such as low education, limited labor, and poor infrastructure that can limit yield growth. This study contributes to ongoing discussions on how to better support smallholder farmers across the region by identifying the factors that affect agricultural productivity.

The remainder of the paper is structured as follows. Chapter 2 describes the dataset and key plot and household characteristics. Chapter 3 presents the six estimation strategies used to measure productivity trends at the plot-, household-, plot manager-, and cluster-level. Chapter 4 discusses the main findings in three parts: (1) trends in agricultural productivity, (2) factors associated with unchanging yields across different levels, and (3) a comparison with the findings of Wollburg et al. (2024). Finally, Chapter 5 concludes.

Chapter 2

Data

To examine productivity trends among smallholder crop producers, we use the World Bank's Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) data. We complement these household data with rainfall and temperature data from Earth Observation (EO) remote sensing sources.[1]

2.1 Household Survey Data

The World Bank LSMS-ISA is a household survey program that supports national statistical offices in Sub-Saharan Africa in designing and implementing national household surveys focusing on agriculture. These surveys integrate agricultural data into traditional household surveys to better capture the links between agriculture, livelihoods, and rural development. This data includes information on agricultural input use and output at the individual plot level for each agricultural season.

The statistical offices of Ethiopia, Malawi, Mali, Niger, Nigeria, and Tanzania collected data spanning from 2008 to 2021, with each country contributing at least two waves corresponding to a country-specific agricultural production season. Figure 2.1 provides a visual representation of the LSMS-ISA timeline across countries.

In Ethiopia, the data comes from the Ethiopia Socioeconomic Survey (ESS), conducted by the Central Statistical Agency of Ethiopia (CSA) in multiple waves (2011/2012, 2013/2014, 2015/2016, 2018/2019, 2020/2021). Households are not tracked for more than three waves and the panel was completely refreshed in wave 4. Across these five waves, the dataset includes a total of 49,172 plots from 5,196 households.

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[1] Appendix A.2 presents alternative analyses using rainfall metrics from two other EO remote sensing sources.

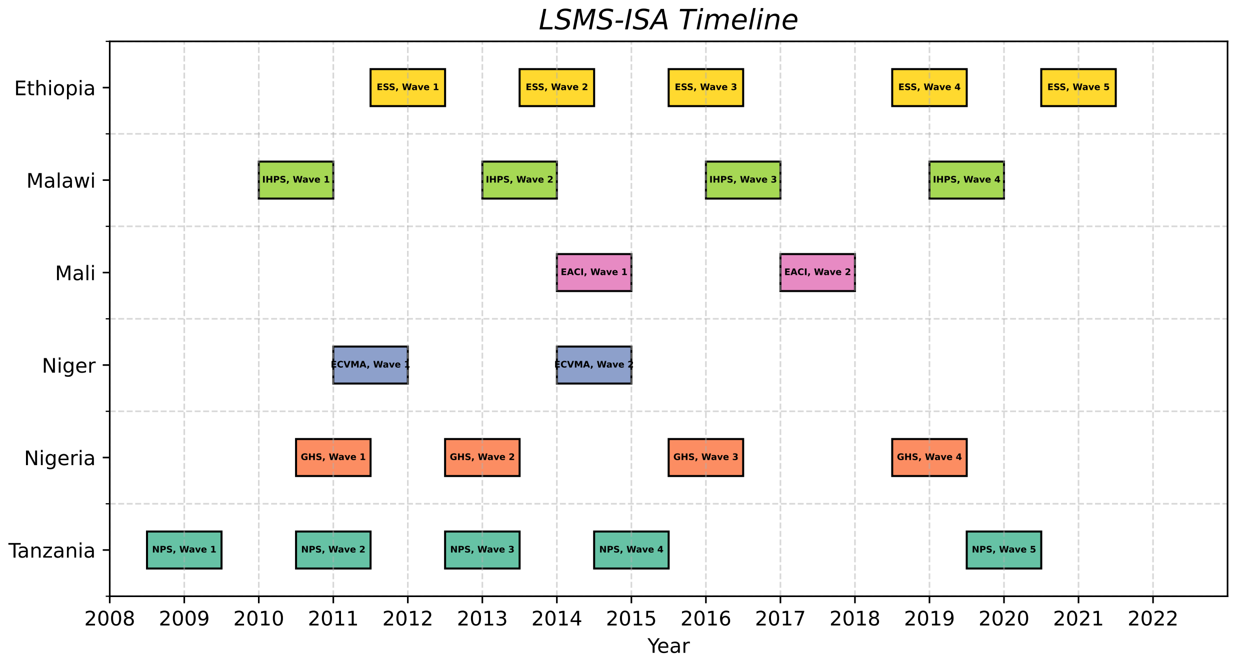

Figure 2.1: LSMS-ISA Timeline across Sub-Saharan Countries.

For Malawi, we use data from four waves of the Integrated Household Panel Survey (IHPS), conducted by the National Statistic Office (NSO) in 2010/2011, 2013/2014, 2016/2017, and 2019/2020. We use 29,669 plots from approximately 4,300 households.

In Mali, we use data from two waves of the Enquête Agricole de Conjoncture Intégrée (EACI), covering 2014 and 2017. Households are not followed through time since the Enumeration Area (EA) is the smallest tracking unit.[2] Across these two waves, the dataset includes 12,032 plots from 3,711 households.

For Niger, data were drawn from the Enquête National sur les Conditions de Vie des Ménages et Agriculture (ECVMA). We use two waves from 2011 and 2014. We use 16,821 plots from 2,223 households.

In Nigeria, we use four waves of the General Household Survey (GHS), covering the periods 2010/2011, 2012/2013, 2015/2016, and 2018/2019. The panel underwent a partial refresh in wave 4. Across these four waves, the dataset includes 32,775 plots from 5,637 households.

In Tanzania, we use five waves of the National Panel Survey (NPS), covering the periods 2008/2009, 2010/2011, 2012/2013, 2014/2015, and 2019/2020. In wave 4 (2014/2015), a

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[2] EAs are geographic areas defined by survey boundaries, used to group households in one area.

refresh sample was added to the panel and re-interviewed in 2020/2021 as part of wave 5. We use 20,311 plots from 5,419 households.

For our analysis, we use a cross-country panel dataset, which is a crop-, plot-, plot manager-, and household-level dataset, compiled and created by Bentze (2024) and Bentze and Wollburg (2024). It compiles a set of agricultural variables from the LSMS-ISA. The dataset focuses on households involved in agricultural activities, resulting in over 160,000 plot observations from approximately 26,500 households. We use this compiled dataset as the base for this work.

To measure smallholder crop productivity, we use yield, which is defined as the value of output per hectare (USD/ha). Each crop value is first converted from local currency to 2020 USD using an exchange rate from the World Bank's World Development Indicators (World Bank, 2024). We then recalculate harvest values using constant prices.[3] Following Wollburg et al. (2023), we use constant prices to ensure that year-to-year changes in crop prices do not create fluctuations in yield values, which could affect productivity trend estimates.

Further, there is substantial heterogeneity in cropping patterns both within and across countries, largely because households often grow multiple crops or vary their crops across different agricultural seasons. We address this variation by identifying the main crop at each level of aggregation. The main crop is defined as the crop with the highest value at the respective level (plot, household, plot manager, or cluster)[4]. We control for this variation by classifying the main crop into one of the twelve crop categories listed in Figure 2.2, which gives us a visual representation of the variation in crop production. These crop categories include staple cereals, legumes, root crops, and seeds. We also define a "cash crop" category, which consists of crops such as cotton and tobacco, as well as a separate category for fruit trees.

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[3] Country-specific prices are calculated in the following way: First, we select a base year for each country. Next, we compute per-unit prices by dividing the harvest value by the quantity for each crop, resulting in multiple per-unit prices per crop (USD/kg). If there are more than ten transactions within an enumeration area (EA), we use the EA-level median price; otherwise, we use the country-level median. We then multiply the selected median price by the harvest quantity to obtain the crop's value at constant price. This same price is applied across all waves within the country. We use the same procedure to compute the constant-price values of seed and inorganic fertilizer.

[4] As intercropping is common in the region, many households grow multiple crops on a single plot. For this reason, it is possible to identify a main crop at the plot level.

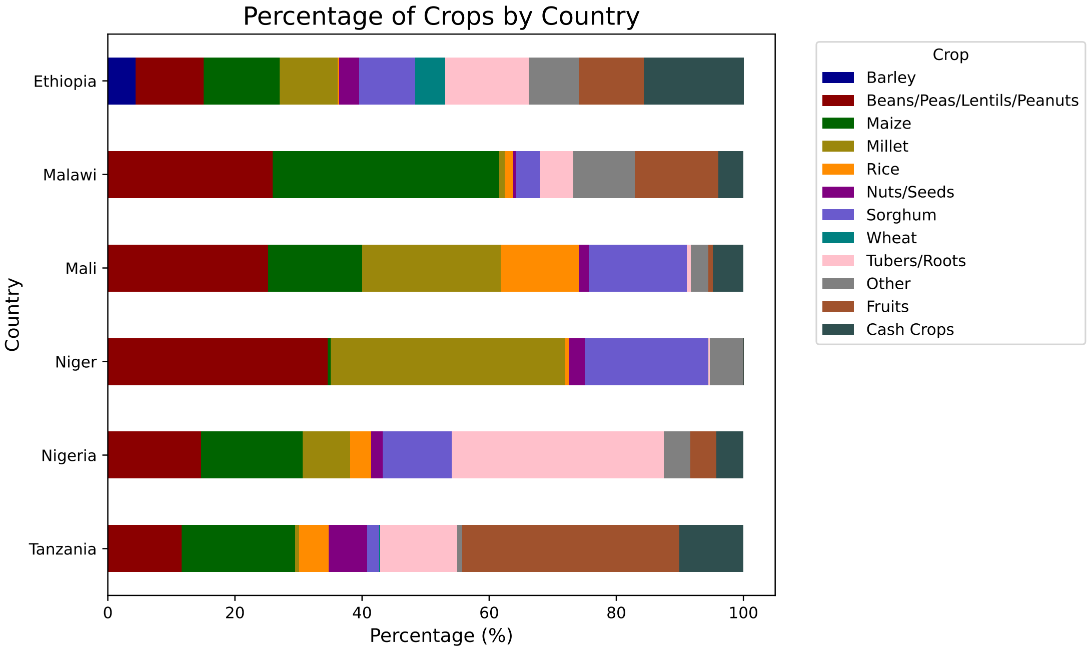

Figure 2.2: Crop category distribution by country.

In our analysis, we also include agricultural inputs. These are presented in Table 2.1 in Section 2.2. Inputs used include the value of inorganic fertilizer and seeds and the total labor days per plot. All input variables, except for labor, are valued at constant USD prices; missing values and outliers above the 95th percentile are imputed, except for plot area.[5] We impute only the top 5% to account for real zeros, such as the well-documented non-use of fertilizer in SSA (Johnson et al., 2023).[6] In addition, we include variables at the plot, manager, and household scales. The plot variables include indicator variables for the use of pesticides and organic fertilizer, irrigation, intercropping, ownership status, and exposure to agricultural shocks. Household variables account for access to electricity, household shocks, which is measured as the death of a family member, a count of household size, and whether the household is located in a rural or urban area. Plot manager variables include the plot manager's age, an indicator identifying whether the plot manager has any formal education, and if the plot manager is a woman. The variables of interest are discussed further in Section 2.2.

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[5] Plot area is already imputed in the cross-country panel dataset by Bentze (2024).

[6] We only impute harvest value for observations that had recorded harvest quantities. If harvest quantity was entirely missing, we do not retain the imputed harvest value and instead leave them as missing.

2.2 Descriptive Statistics

In this section, we summarize and describe plot, household, and plot manager characteristics across the countries included in our analysis. We focus on the variables of interest and highlight only those characteristics that show variation, over time and within a country. Summary statistics are presented in Tables 2.1 to 2.6.

2.2.1 Input Use

Trends in input use vary across countries. In Ethiopia, pesticide use has increased steadily across time, with an average growth of about 10% per wave. This aligns with broader patterns encouraging adoption of modern inputs, in particular aimed at reducing yield losses from pests and diseases. In Malawi, the use of organic fertilizer has doubled from being used on only 12% to being used on 24% of plots. This raises questions about its potential impact on productivity, though also questions about the use of organic rather than Nitrogen or inorganic fertilizer, particularly given the widespread fertilizer programs in the country (Benson et al., 2024; Ricker-Gilbert, 2014; Ricker-Gilbert and Jayne, 2011). Mali shows an increase in seed expenditure, with nearly $10 more spent per hectare across waves. This suggests a dramatic increase in input use. In contrast, Niger presents an exception to regional trends, with seed use decreasing by approximately 60% across waves.

2.2.2 Household Characteristics

Turning to farm characteristics, we observe changes in the size and use of farmland. In Tanzania, average plot size increases over time, possibly due to land consolidation (Sullivan et al., 2024; Gil, 2022). Conversely, both Mali and Niger experience a decline in both plot and farm sizes, which might be explained by an increase in rural density in these countries (Josephson et al., 2014; Ricker-Gilbert et al., 2014). It is interesting to note that the stability in the number of plots held per household across survey waves, as the average number of plots within each country shows little variation over time.

We also consider access to electricity, which is a proxy for rural infrastructure (World Bank, 2011). It has improved meaningfully in multiple countries. In Ethiopia, coverage rose from 8% of plots in wave 1 to 63% in the most recent wave in 2021. Malawi also saw a steady increase from 3% to 8%. These changes potentially reflect national efforts within these countries to improve access to electricity and other basic infrastructure in rural areas, which may have positive spillovers onto agricultural productivity trends.

2.2.3 Plot Manager Traits

Finally, we identify trends in plot manager traits, such as formal education and gender of the manager of the plot. The education of the plot manager shows interesting variation within countries. In Ethiopia, the share of plots managed by individuals with formal education rose from 32% to approximately 44% across all rounds. Nigeria shows a particularly striking change: the share of formally educated managers rose from 17% to 74% over the survey period. These trends may reflect better access to education within the region, which may translate into higher yields (Reimers and Klasen, 2013).

There is a general upward trend in the share of women-managed plots across most countries, which aligns with recent literature highlighting the feminization of agricultural activities in the region, as women become more visible in agricultural activities (Kawarazuka et al., 2022; Leder, 2022; Najjar, 2021; Slavchevska et al., 2019). In Malawi, the share of women-managed plots grew from 29% to 43%, and in Mali, it nearly tripled across two survey waves. Tanzania also experiences an increase in women-managed plots from 23% to 30%. However, Niger again differs from the regional trend, showing a decline in women-managed plots over time, from 17% to 13%.

2.2.4 Weather

We use LASSO regression to select weather variables based on their predictive power, allowing us to focus on the most relevant weather-related metrics for explaining yield outcomes. More details on weather variable selection are provided in Appendix A.1.

The selected variables capture not only average weather conditions but also major shifts in temperature and rainfall. For instance, maximum daily temperature may better reflect heat stress than average temperature, especially at key points in the growing season. The number of no rain days highlights dry spells, which can affect crops even if there is enough total rain in the season. Finally, the skewness of daily temperature captures the asymmetry of the temperature distribution; for example, this metric could indicate that extreme heat is common, even if average temperatures do not appear too high.

These weather metrics are particularly important for smallholder agriculture, where crops are highly sensitive to unpredictable or extreme weather events. Including them in the model helps us better capture the weather-related risks that affect crop yields.

Table 2.1: Summary Statistics for Plots in Ethiopia

		Wave 1		Wave 2		Wave 3		Wave 4		Wave 5	
		Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
Category	Variable										
Plot Level	Any Crop Intercropped (Yes/No)	0.20	0.40	0.30	0.46	0.25	0.43	0.29	0.45	0.34	0.47
	Inorganic Fertilizer ($/ha)	63.46	511.70	71.68	826.64	580.68	10,872.47	305.33	6,987.57	1,088.11	27,155.43
	Is the Plot Irrigated? (Yes/No)	0.03	0.16	0.03	0.17	0.03	0.16	0.03	0.17	0.03	0.17
	Organic Fertilizer Use (Yes/No)	0.20	0.40	0.28	0.45	0.24	0.43	0.32	0.47	0.38	0.49
	Pesticide Use (Yes/No)	0.02	0.15	0.03	0.17	0.04	0.19	0.05	0.21	0.05	0.22
	Plot Size (ha)	0.19	0.37	0.22	1.02	0.23	3.61	0.15	0.22	0.14	0.24
	Seed ($/ha)	92.68	942.36	181.18	2,738.29	115.49	2,574.23	526.08	12,350.09	233.39	2,103.33
	Total Labor Days (days/ha)	667.65	2,628.97	2,690.53	118,084.28	964.98	11,268.14	2,913.50	62,979.23	3,268.11	19,497.87
	Yield ($/ha)	915.93	4,709.40	1,536.31	43,940.64	1,464.87	41,037.42	1,199.42	9,154.98	1,942.98	17,547.39
Household Level	Electricity Access (Yes/No)	0.08	0.27	0.14	0.35	0.31	0.46	0.46	0.50	0.63	0.48
	Farm Size (ha)	2.10	2.84	2.13	4.73	2.18	8.46	1.35	1.44	1.40	1.41
	Household Shock (Yes/No)	0.40	0.49	0.34	0.47	0.63	0.48	0.38	0.48	0.67	0.47
	Household Size	5.49	2.16	5.61	2.20	5.66	2.21	5.20	2.09	5.45	2.16
	Number of Plots	14.47	8.05	14.23	7.61	14.72	7.86	11.72	6.24	13.55	7.52
Farmer Level	Age (years)	45.03	14.71	46.54	14.57	48.04	14.38	46.09	14.60	46.85	14.39
	Any Formal Education (Yes/No)	0.32	0.46	0.33	0.47	0.34	0.47	0.37	0.48	0.44	0.50
	Is the Plot Manager Female? (Yes/No)	0.13	0.34	0.16	0.36	0.14	0.35	0.15	0.36	0.17	0.38
Weather	Maximum Daily Temperature (°C)	23.63	3.02	23.03	2.97	23.49	2.89	23.49	3.52	22.62	2.95
	No Rain Days	87.01	22.06	88.31	21.78	92.67	24.90	80.32	20.80	87.97	23.49
	Skew of Daily Temperature	0.25	0.14	0.11	0.17	0.11	0.13	0.20	0.15	0.05	0.18
Observations	N	3,063	3,063	15,563	15,563	14,111	14,111	9,216	9,216	7,219	7,219

Table 2.2: Summary Statistics for Plots in Mali

		Wave 1		Wave 2	
		Mean	St. Dev	Mean	St. Dev
Category	Variable				
Plot Level	Any Crop Intercropped (Yes/No)	0.14	0.34	0.09	0.28
	Inorganic Fertilizer ($/ha)	460.54	17,589.19	32.94	827.06
	Is the Plot Irrigated? (Yes/No)	0.00	0.04	0.04	0.20
	Organic Fertilizer Use (Yes/No)	0.50	0.50	0.41	0.49
	Pesticide Use (Yes/No)	0.06	0.23	0.06	0.24
	Plot Size (ha)	3.36	9.34	1.80	2.22
	Seed ($/ha)	13.04	124.09	23.57	147.61
	Total Labor Days (days/ha)	1,032.65	9,396.21	329.69	1,275.65
	Yield ($/ha)	457.10	2,314.08	512.64	6,115.62
Household Level	Electricity Access (Yes/No)	0.41	0.49	0.77	0.42
	Farm Size (ha)	17.73	40.34	9.24	7.67
	Household Shock (Yes/No)	0.72	0.45	0.86	0.35
	Household Size	13.68	9.39	13.65	8.99
	Number of Plots	6.19	3.51	5.35	3.09
Farmer Level	Age (years)	50.56	14.44	49.78	14.48
	Any Formal Education (Yes/No)	0.14	0.35	0.14	0.34
	Is the Plot Manager Female? (Yes/No)	0.05	0.21	0.14	0.35
Weather	Maximum Daily Temperature (°C)	35.45	1.96	35.93	2.19
	No Rain Days	115.51	13.77	117.32	12.21
	Skew of Daily Temperature	-0.08	0.12	-0.09	0.11
Observations	N	3,936	3,936	8,095	8,095

Table 2.3: Summary Statistics for Plots in Niger

		Wave 1		Wave 2	
		Mean	St. Dev	Mean	St. Dev
Category	Variable				
Plot Level	Any Crop Intercropped (Yes/No)	0.84	0.36	0.89	0.32
	Inorganic Fertilizer ($/ha)	141.26	9,134.37	3.94	128.23
	Is the Plot Irrigated? (Yes/No)	0.01	0.10	0.02	0.15
	Organic Fertilizer Use (Yes/No)	0.37	0.48	0.44	0.50
	Pesticide Use (Yes/No)	0.01	0.08	0.06	0.23
	Plot Size (ha)	2.65	6.14	2.20	3.96
	Seed ($/ha)	56.95	1,841.47	19.22	499.64
	Total Labor Days (days/ha)	1,907.54	33,986.13	609.14	12,280.90
	Yield ($/ha)	1,428.53	36,013.86	529.31	11,307.89
Household Level	Electricity Access (Yes/No)	0.07	0.25	0.07	0.26
	Farm Size (ha)	9.06	15.89	6.97	8.69
	Household Shock (Yes/No)	0.70	0.46	0.68	0.47
	Household Size	7.28	3.71	8.49	4.17
	Number of Plots	3.94	2.30	3.55	2.16
Farmer Level	Age (years)	43.78	14.67	45.97	14.30
	Any Formal Education (Yes/No)	0.15	0.35	0.14	0.34
	Is the Plot Manager Female? (Yes/No)	0.17	0.38	0.13	0.34
Weather	Maximum Daily Temperature (°C)	35.49	0.96	34.95	0.78
	No Rain Days	76.01	6.39	72.50	9.16
	Skew of Daily Temperature	-0.02	0.06	0.07	0.06
Observations	N	9,570	9,570	7,251	7,251

Table 2.4: Summary Statistics for Plots in Malawi

		Wave 1		Wave 2		Wave 3		Wave 4	
		Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
Category	Variable								
Plot Level	Any Crop Intercropped (Yes/No)	0.54	0.50	0.62	0.49	0.65	0.48	0.76	0.43
	Inorganic Fertilizer ($/ha)	452.07	838.52	560.81	2,822.78	416.64	1,075.58	388.80	1,248.06
	Is the Plot Irrigated? (Yes/No)	0.01	0.08	0.01	0.10	0.01	0.08	0.01	0.09
	Organic Fertilizer Use (Yes/No)	0.12	0.32	0.16	0.37	0.21	0.41	0.24	0.43
	Pesticide Use (Yes/No)	0.01	0.11	0.02	0.13	0.02	0.15	0.03	0.18
	Plot Size (ha)	0.51	5.88	0.54	6.02	0.36	0.38	0.31	0.32
	Seed ($/ha)	31.85	143.12	39.32	581.17	30.92	172.54	47.74	529.97
	Total Labor Days (days/ha)	267.45	478.72	360.48	838.63	314.75	450.63	260.84	700.48
	Yield ($/ha)	398.11	952.76	507.26	2,536.50	338.11	2,645.31	1,055.10	54,109.25
Household Level	Electricity Access (Yes/No)	0.03	0.18	0.05	0.22	0.07	0.26	0.08	0.27
	Farm Size (ha)	1.49	22.57	1.74	10.43	1.26	1.89	1.28	1.50
	Household Shock (Yes/No)	0.77	0.42	0.98	0.14	1.00	0.01	0.89	0.32
	Household Size	5.11	2.30	5.38	2.34	5.23	2.24	5.03	2.22
	Number of Plots	2.38	1.43	2.25	1.28	2.93	1.98	3.26	2.38
Farmer Level	Age (years)	42.92	15.96	44.08	15.82	43.70	15.58	43.85	16.01
	Any Formal Education (Yes/No)	0.81	0.40	0.82	0.39	0.87	0.33	0.86	0.35
	Is the Plot Manager Female? (Yes/No)	0.29	0.46	0.30	0.46	0.40	0.49	0.43	0.49
Weather	Maximum Daily Temperature (°C)	26.70	2.25	27.76	2.04	29.24	2.01	28.05	1.83
	No Rain Days	100.44	13.27	103.50	10.54	117.73	12.40	86.87	8.75
	Skew of Daily Temperature	0.01	0.07	0.04	0.05	0.04	0.06	0.09	0.05
Observations	N	6,487	6,487	9,098	9,098	5,310	5,310	8,774	8,774

Table 2.5: Summary Statistics for Plots in Nigeria

		Wave 1		Wave 2		Wave 3		Wave 4	
Category	Variable	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
Plot Level	Any Crop Intercropped (Yes/No)	0.83	0.38	0.83	0.38	0.79	0.41	0.70	0.46
	Inorganic Fertilizer ($/ha)	2,639.54	150,729.14	349.29	4,275.60	169.36	834.64	1,915.47	116,644.50
	Is the Plot Irrigated? (Yes/No)	0.03	0.16	0.01	0.12	0.01	0.11	0.02	0.14
	Organic Fertilizer Use (Yes/No)	0.03	0.16	0.04	0.20	0.31	0.46	0.14	0.35
	Pesticide Use (Yes/No)	0.18	0.39	0.18	0.38	0.23	0.42	0.14	0.35
	Plot Size (ha)	0.72	1.17	0.56	0.97	0.52	0.76	0.57	1.08
	Seed ($/ha)	654.24	21,636.42	532.58	9,516.99	643.94	6,933.96	1,839.48	34,734.07
	Total Labor Days (days/ha)	5,500.63	305,487.31	2,411.78	5,887.81	2,591.29	11,730.15	2,893.27	7,619.75
	Yield ($/ha)	13,211.15	668,562.26	1,557.87	9,701.59	2,533.19	16,013.47	7,120.19	619,162.46
Household Level	Electricity Access (Yes/No)	0.24	0.43	0.32	0.47	0.41	0.49	0.40	0.49
	Farm Size (ha)	1.53	2.05	1.16	2.04	1.20	1.69	1.78	2.26
	Household Shock (Yes/No)	0.33	0.47	0.46	0.50	0.26	0.44	0.30	0.46
	Household Size	5.48	2.90	6.76	3.35	6.88	3.31	6.54	3.62
	Number of Plots	2.31	1.48	2.25	1.20	2.35	1.25	3.84	2.08
Farmer Level	Age (years)	48.20	14.60	51.41	14.45	52.20	13.85	49.65	14.56
	Any Formal Education (Yes/No)	0.14	0.34	0.21	0.41	0.61	0.49	0.74	0.44
	Is the Plot Manager Female? (Yes/No)	0.12	0.33	0.17	0.37	0.16	0.36	0.20	0.40
Weather	Maximum Daily Temperature (°C)	30.27	2.47	29.23	1.80	30.41	2.19	30.12	2.28
	No Rain Days	57.20	13.10	61.01	15.13	68.91	20.65	59.00	13.17
	Skew of Daily Temperature	0.13	0.11	0.10	0.09	0.18	0.10	0.10	0.08
Observations	N	4,957	4,957	8,142	8,142	7,936	7,936	11,740	11,740

Table 2.6: Summary Statistics for Plots in Tanzania

		Wave 1		Wave 2		Wave 3		Wave 4		Wave 5	
		Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
Category	Variable										
Plot Level	Any Crop Intercropped (Yes/No)	0.74	0.44	0.76	0.43	0.72	0.45	0.73	0.44	0.63	0.48
	Inorganic Fertilizer ($/ha)	13.29	72.13	300.88	7,524.27	12.17	135.71	17.73	232.36	22.67	379.77
	Is the Plot Irrigated? (Yes/No)	0.04	0.20	0.04	0.19	0.02	0.14	0.01	0.11	0.01	0.09
	Organic Fertilizer Use (Yes/No)	0.16	0.36	0.13	0.34	0.14	0.35	0.16	0.36	0.18	0.39
	Pesticide Use (Yes/No)	0.17	0.38	0.13	0.34	0.11	0.31	0.13	0.34	0.21	0.40
	Plot Size (ha)	1.14	1.75	1.34	2.52	1.65	4.05	1.71	3.79	4.77	175.43
	Seed ($/ha)	25.18	87.36	22.87	93.66	28.41	161.93	21.77	85.45	39.54	408.37
	Total Labor Days (days/ha)	460.33	4,444.11	182.14	349.77	241.51	1,024.61	218.48	926.70	209.41	965.63
	Yield ($/ha)	811.70	14,119.13	3,127.14	99,419.22	296.57	6,284.65	251.70	806.78	521.09	7,700.42
Household Level	Electricity Access (Yes/No)	0.06	0.23	0.09	0.29	0.10	0.30	0.21	0.41	0.62	0.48
	Farm Size (ha)	2.44	2.89	3.20	5.60	3.84	8.19	3.36	5.16	10.95	322.23
	Household Shock (Yes/No)	0.69	0.46	0.59	0.49	0.53	0.50	0.83	0.38	0.64	0.48
	Household Size	5.70	3.29	6.19	3.68	6.07	3.63	5.99	3.55	6.11	3.65
	Number of Plots	2.53	1.43	2.66	1.59	2.80	1.60	2.61	1.58	2.60	1.51
Farmer Level	Age (years)	45.48	14.53	46.63	14.28	49.06	15.66	46.87	14.78	48.60	14.65
	Any Formal Education (Yes/No)	0.77	0.42	0.76	0.42	0.74	0.44	0.73	0.44	0.75	0.43
	Is the Plot Manager Female? (Yes/No)	0.23	0.42	0.24	0.43	0.25	0.43	0.26	0.44	0.30	0.46
Weather	Maximum Daily Temperature (°C)	26.28	2.11	26.54	2.22	26.38	2.21	26.32	2.17	25.91	2.14
	No Rain Days	113.19	27.43	114.74	22.15	112.39	23.06	116.42	20.29	100.78	21.26
	Skew of Daily Temperature	0.02	0.12	0.05	0.14	0.04	0.11	0.07	0.11	0.01	0.10
Observations	N	1,399	1,399	1,433	1,433	6,556	6,556	5,777	5,777	5,146	5,146

Chapter 3

Methodology

We estimate six specifications to identify productivity trends across SSA. These specifications are modeled at different levels of aggregation. Models 1 and 2 are at the plot-level, Models 3 and 4 are at the household-level, Model 5 is at the plot manager-level, and Model 6 is at the cluster-level.

Model 2, specified at the plot-level, serves as the baseline for deriving models at different levels of aggregation. To transition from the plot-level to the household, plot manager, and cluster levels, we aggregate the data as follows: input and output values at constant prices are summed across all plots associated with each level (e.g., household, plot manager, or cluster). For indicator variables, we assign a representative value. For instance, when determining the main crop fixed effect at a given level, we identify the crop with the highest total value at constant prices across all relevant plots within a household, plot manager, or cluster and classify it into one of the crop categories previously mentioned in Section 2.1. This is standard for some variables at the cluster-level (Model 6). For other variables at the cluster-level, we instead use the mean of the binary variable, which represents the proportion of plots within the cluster exhibiting that characteristic. For example, in the case of plot manager gender, we calculate the mean of the variable across households within a cluster, resulting in the percentage of woman-managed plots. One notable exception is made for agro-ecological zones, which are represented by the zone that appears most frequently within each cluster.[1]

In Model 1, we use a naïve linear model at the plot-level where we regress yield on an annual time trend and country fixed effects. Model 1 is written:

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[1] We control for agro-ecological zones in Models 2 through 6. These are included as part of the household variables matrix.

$$\ln(Y_{it}) = \alpha + \beta\, year_t + C_c + \epsilon_{it}, \tag{1}$$

where Y refers to yield, the value of output per hectare using constant prices, which is how we measure productivity at the smallholder level over time; α is the constant term, *year* is the continuous time trend, C refers to the country fixed effects, and ϵ is the error term.[2] In all of specifications, β is our coefficient of interest, which captures changes in productivity, at different levels of aggregation, over time.

Model 2 follows the same structure as Model 1. However, we extend and include matrices of agricultural inputs and variables for plot, household, and plot manager traits, which are represented by the subscripts *i, h*, and *j*, respectively. We also include rainfall and temperature metrics; main crop fixed effects; and country fixed effects. This specification is written:

$$\begin{aligned}\ln(Y_{it}) = \alpha + \beta\,\text{year}_t + \underbrace{\sum_{a=1}^{A}\delta_{ait}\ln(S_{ait})}_{\text{Agricultural inputs}} + \underbrace{\sum_{v=1}^{V}\gamma_{vit}(W_{vit})}_{\text{Plot Variables}} + \underbrace{\sum_{l=1}^{L}\theta_{lht}(X_{lht})}_{\text{Household Variables}} + \underbrace{\sum_{g=1}^{G}\psi_{gjt}(Z_{gjt})}_{\text{Plot manager Variables}} \\ + \underbrace{\sigma_{ht}R_{ht}}_{\text{Weather Metrics}} + \underbrace{M_{it}}_{\text{Main Crop Fixed Effects}} + \underbrace{C_c}_{\text{Country Fixed Effects}} + \underbrace{\epsilon_{it}}_{\text{Error Term}},\end{aligned} \tag{2}$$

where S is a matrix of scaled agricultural inputs indexed by l. The matrices W, X, and Z denote variables for plot, household, and plot manager traits, respectively. Tables 2.1 to 2.6 shown above demonstrate the specific variables for each matrix. R is a set of rainfall and temperature metrics, which were selected based on LASSO, described in more detail in Appendix A.1. M_{it} represents the indicator variables for main crop fixed effects at the plot-level, and ϵ represents the error term. It is worth noting that we also estimated Models 1 and 2 separately for each country to explore productivity trends within the six SSA countries included in this study.

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[2] Although the equations present variables in logarithmic form (e.g., $\ln(Y_{it})$), we use the inverse hyperbolic sine (asinh) transformation for outcome and input variables in the analysis. The asinh transformation is similar to the natural log for large values but is defined at zero and handles zeros and negative values more appropriately.

Model 2 serves as the baseline for the construction of other specifications. Model 3 estimates agricultural productivity by aggregating information at the plot-level (e.g., agricultural inputs, output value, control variables) to the household-level h. Model 3 is written:

$$\ln(Y_{ht}) = \alpha + \beta\,\text{year}_t + \underbrace{\sum_{a=1}^{A} \delta_{aht} \ln(S_{aht})}_{\text{Agricultural inputs}} + \underbrace{\sum_{v=1}^{V} \gamma_{vit}(W_{vit})}_{\text{Plot Variables}} + \underbrace{\sum_{l=1}^{L} \theta_{lht}(X_{lht})}_{\text{Household variables}} + \underbrace{\sum_{g=1}^{G} \psi_{gjt}(Z_{gjt})}_{\text{Plot manager Variables}}$$
$$+ \underbrace{\sigma_{ht} R_{ht}}_{\text{Weather Metrics}} + \underbrace{M_{ht}}_{\text{Main Crop Fixed Effects}} + \underbrace{C_c}_{\text{Country Fixed Effects}} + \underbrace{\epsilon_{ht}}_{\text{Error Term}}, \tag{3}$$

Model 4 measures agricultural productivity at the household-level and includes household fixed effects. This means that the constant term α_h, varies from household to household. This specification is written:

$$\ln(Y_{ht}) = \alpha_h + \beta\,\text{year}_t + \underbrace{\sum_{a=1}^{A} \delta_{aht} \ln(S_{aht})}_{\text{Agricultural inputs}} + \underbrace{\sum_{v=1}^{V} \gamma_{vit}(W_{vit})}_{\text{Plot Variables}} + \underbrace{\sum_{l=1}^{L} \theta_{lht}(X_{lht})}_{\text{Household Variables}} + \underbrace{\sum_{g=1}^{G} \psi_{gjt}(Z_{gjt})}_{\text{Plot manager Variables}}$$
$$+ \underbrace{\sigma_{ht} R_{ht}}_{\text{Weather Metrics}} + \underbrace{M_{ht}}_{\text{Main Crop Fixed Effects}} + \underbrace{\epsilon_{ht}}_{\text{Error Term}}, \tag{4}$$

Model 5 is aggregated at the plot manager-level j. In this specification, we include plot manager fixed effects, where the intercept α_j, changes from one plot manager to another. Model 5 is written:

$$\ln(Y_{jt}) = \alpha_j + \beta\,\text{year}_t + \underbrace{\sum_{a=1}^{A} \delta_{ajt} \ln(S_{ajt})}_{\text{Agricultural inputs}} + \underbrace{\sum_{v=1}^{V} \gamma_{vit}(W_{vit})}_{\text{Plot Variables}} + \underbrace{\sum_{l=1}^{L} \theta_{lht}(X_{lht})}_{\text{Household Variables}} + \underbrace{\sum_{g=1}^{G} \psi_{gjt}(Z_{gjt})}_{\text{Plot manager Variables}}$$
$$+ \underbrace{\sigma_{ht} R_{ht}}_{\text{Weather Metrics}} + \underbrace{M_{jt}}_{\text{Main Crop Fixed Effects}} + \underbrace{\epsilon_{jt}}_{\text{Error Term}}. \tag{5}$$

Models 4, 5, and 6 do not include country fixed effects, unlike the main specification (Model 2), because household, plot manager, and cluster fixed effects in these models already absorb unobserved country-specific heterogeneity. In Models 4 and 5, we omit observations from Mali as households and plot managers cannot be tracked over time in that country.

Finally, Model 6 measures agricultural productivity at the cluster-level k. This specification includes cluster fixed effects, which control for unobserved characteristics shared by plots within the same cluster. Model 6 is written:

$$\ln(Y_{kt}) = \alpha_k + \beta\,\text{year}_t + \underbrace{\sum_{a=1}^{A} \delta_{akt} \ln(S_{akt})}_{\text{Agricultural inputs}} + \underbrace{\sum_{v=1}^{V} \gamma_{vit}(W_{vit})}_{\text{Plot Variables}} + \underbrace{\sum_{l=1}^{L} \theta_{lht}(X_{lht})}_{\text{Household Variables}} + \underbrace{\sum_{g=1}^{G} \psi_{gjt}(Z_{gjt})}_{\text{Plot manager Variables}}$$
$$+ \underbrace{\sigma_{kt} R_{kt}}_{\text{Weather Metrics}} + \underbrace{M_{kt}}_{\text{Main Crop Fixed Effects}} + \underbrace{\epsilon_{kt}}_{\text{Error Term}}, \tag{6}$$

All models use clustered standard errors, clustered at the Enumeration Area (EA) level. All models also are weighted using population weights to ensure that the estimates are representative of the country. The weights are adjusted, relative to the level of aggregation. At the plot-level (Models 1 and 2), household weights are divided by the number of plots within each household to distribute the household's weight across its plots and ensure that households are not, effectively, double counted. At the household level (Models 3 and 4), we use the original household weights provided in the survey, without adjustment. For Model 5, at the plot manager-level, household weights are divided by the number of plot managers within each household to again ensure equal distribution and mitigate double counting. Finally, for the cluster-level analysis in Model 6, weights are aggregated by adding all household weights within a cluster.[3]

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[3] In the fixed effects models (Models 4 to 6), we use bootstrap resampling weights to account for the uncertainty arising from the sampling design and the estimation of post-stratification weights. Specifically, we implement a bootstrap procedure with 500 resamples of the weights. This approach allows us to capture variability from both the sampling process and the construction of the weights, resulting in more accurate standard errors.

Chapter 4

Results

We explore agricultural productivity trends across SSA at different levels: plot (Models 1 and 2), household (Models 3 and 4), plot manager (Model 5), and cluster (Model 6). Examining productivity trends at these levels allows us to understand the effect of investments aimed at improving agricultural productivity.

In this section, we present the results of our analysis, organized into three subsections. First, we examine trends in agricultural productivity over time. Next, we identify the associated effect of key factors on crop yields at the different levels of aggregation. Finally, we compare our findings with those of Wollburg et al. (2024) to assess similarities and differences.

4.1 Agricultural Productivity

In this section, we discuss agricultural productivity trends over time, when using the full cross-country sample. We use six regression models to identify productivity trends at different aggregation levels. Figure 4.1 presents a summary of the estimated coefficients, capturing changes in productivity over time at the plot- (Models 1 and 2), household- (Models 3 and 4), plot manager- (Model 5), and cluster-level (Model 6). In the second part of the analysis, we apply Models 1 and 2 separately to each of the six countries. Table 4.1 presents the estimated time trends in productivity for each country.

4.1.1 Aggregation for all of Sub-Saharan Africa

First, Model 1 is a naïve linear model at the plot-level, in which yield is regressed on an annual time trend. Model 2 serves as our baseline specification. This specification includes agricultural inputs, controls, variables at different levels, and weather-related metrics. We find no evidence of improvement in agricultural productivity over time at the plot-level between 2008 and 2021. In Model 1, the estimated coefficient on the time trend is close to zero and statistically insignificant, indicating no meaningful change in productivity. In contrast, Model 2 shows a statistically significant annual decline of 1.97 % in agricultural productivity.

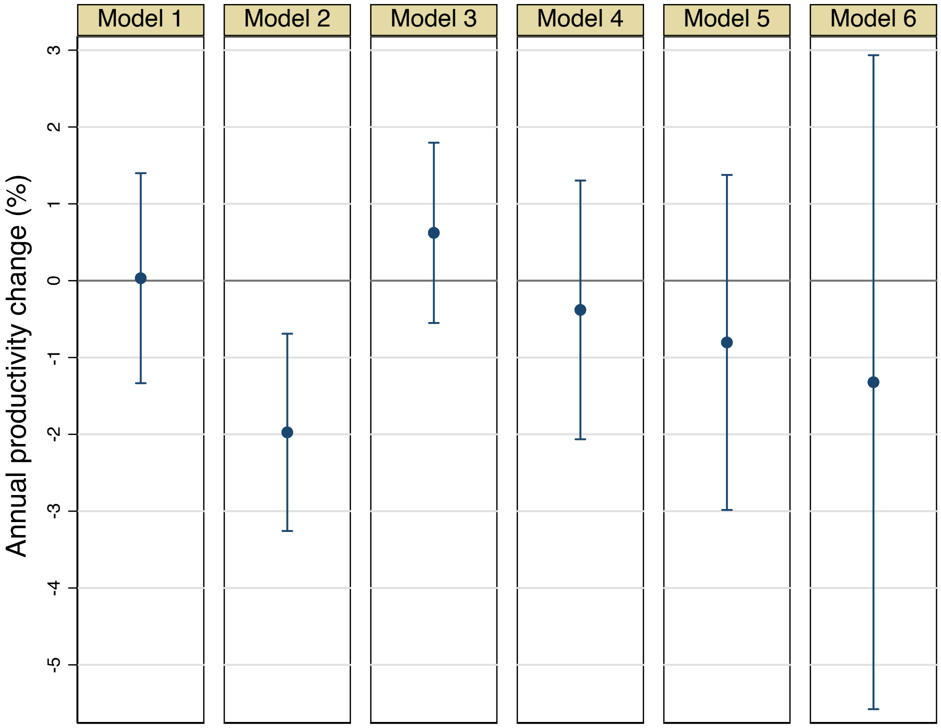

Figure 4.1: Annual productivity estimated coefficients.

Next, we examine Models 3 through 6, which allow us to explore productivity trends at higher levels of aggregation. As shown in Figure 4.1, the confidence intervals around the estimated productivity trends become progressively wider when moving from the plot-level to the household- (Models 3 and 4), plot manager- (Model 5), and cluster-level (Model 6). Specifically, the standard errors of the annual time trend increase from Model 3 to Model 6, as shown in Table 4.2. This suggests a loss of precision and predictive power when aggregating data to higher levels than the plot-level. The uncertainty increases in the estimation productivity trends as additional levels of aggregation are introduced.

Further, aggregating plot-level data to the household-, plot manager-, and cluster-level requires making assumptions about the behavior of these entities, in order to consider the aggregated information as representative. For example, when moving from the plot- to the household-level, input and output values at constant prices are summed across all plots managed by a household. In contrast, for binary and categorical variables, a single representative value is selected. This could involve assigning the crop with the highest value across all plots as the household's main crop, or identifying a household as women-managed if a woman manages at least one plot. This process may result in the loss of relevant information, particularly when assigning a single value to an aggregated trait.

Based on these results, we find no evidence of a change in agricultural productivity over time at the different levels: household (Models 3 and 4), plot manager (Model 5), and cluster (Model 6). This suggests that while plot-level productivity is declining over time, average productivity at other levels is not changing: not declining nor increasing.

The absence of improvement at these levels is concerning, as it indicates that efforts to enhance agricultural productivity may not be translating into broader development outcomes across rural economies in SSA. This stagnation in productivity raises concerns about the effectiveness of current investments and efforts aimed at improving crop productivity in the region. The potential for progress in food security and poverty reduction remains limited if agricultural productivity does not improve, especially at higher levels of aggregation.

4.1.2 Disaggregated, Country-level

We estimate the plot-level Models 1 and 2 separately for each of the six countries included in our analysis. So, instead of specifying one regression with all countries included, we instead specify six separate regressions, with each country separate. Examining each country separately helps us identify changes in crop yields that might be hidden when all countries are combined together. Table 4.1 presents the estimated productivity trends by country.

In Model 1, Malawi shows a statistically significant decline in yields over time. Ethiopia and Nigeria display no significant change in plot-level productivity. In contrast, Mali, Niger, and Tanzania exhibit small but positive trends. When adding explanatory variables and controls in Model 2, these patterns largely remain. However, there are notable changes. For instance, the productivity trend in Malawi becomes insignificant, while Nigeria shifts from no change to a decline in yields.

These results highlight important country-level differences. As seen in Table 4.1, trends vary across countries and may, effectively, cancel each other out when combined at the regional level. This is likely due to our weight adjustments, which ensure representativeness within each country but not across the region. For all intents and purposes, this gives equal weights to plots from countries with very different sample sizes.

As an example, consider: Ethiopia and Nigeria – each with large sample sizes, as shown in Table 4.1 – may have a greater influence on regional estimates. In Model 1, both countries show no significant trends, possibly explaining the overall insignificant result in the the regional aggregation. A similar pattern is observed in Model 2, where the negative regional trend may be largely driven by Nigeria and Malawi, which exhibit declining yields in the disaggregated analysis.

Table 4.1: Country-level results

		Ethiopia	Malawi	Mali	Niger	Nigeria	Tanzania
Model 1	Annual Time Trend	-0.0128	-0.0984**	0.167**	0.387**	-0.0100	0.0519**
		[-0.0450,0.0194]	[-0.117,-0.0801]	[0.0994,0.234]	[0.332,0.442]	[-0.0329,0.0128]	[0.0377,0.0662]
	N	77633	33489	12479	18901	37927	41418
	R^2	0.000	0.029	0.016	0.076	0.000	0.009
Model 2	Annual Time Trend	0.0109	-0.0298**	0.0189	0.329**	-0.0334**	0.0280**
		[-0.0198,0.0417]	[-0.0471,-0.0125]	[-0.102,0.140]	[0.253,0.406]	[-0.0522,-0.0146]	[0.0124,0.0436]
	N	49172	29669	12031	16821	32775	20311
	R^2	0.269	0.506	0.406	0.463	0.575	0.431

95% confidence intervals in brackets

* $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

4.2 Exploring and Understanding Agricultural Productivity

In this section, we identify the factors associated with unchanging yields in SSA over time, building on our analysis in Section 4.1.1. Our analysis focuses on factors associated with plot, household, and plot manager traits and investigates how these different factors are associated with agricultural productivity.[1] We consider a set of variables representative of traits of plots,

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[1] We checked for multicollinearity using the Variance Inflation Factor (VIF) after estimation. None of the main variables showed high VIF values. The highest VIF values were observed in control indicator variables, such as agro-ecological zones, which is not unusual for categorical variables. These were not above 10 (James et al., 2013), which serves as the standard threshold for identifying multicollinearity. Thus, we do not believe that multicollinearity is a problem in our analysis.

households, and plot managers, as shown in Tables 2.1 to 2.6. We focus on these variables, though in our specification we also include weather variables and agro-ecological zones as controls.[2]

We implement this analysis across different levels of aggregation: again at the plot- (Models 1 and 2), household- (Models 3 and 4), plot manager- (Model 5), and cluster-level (Model 6). As a reminder: Model 1 is a naïve linear specification, where plot-level yields are regressed on an annual time trend and country fixed effects. This specification does not include matrices of agricultural inputs, weather-related metrics, variables at different levels, and controls. Again, Model 2 serves as our baseline specification and is used as the primary point of reference for comparison across models.

4.2.1 Plot Variables

At the lowest level of aggregation, Model 2, we find that agricultural inputs have a positive and statistically significant relationship with agricultural productivity. We find that a 1% increase in seed value is associated with a 0.16% increase in yield, while a 1% increase in fertilizer value corresponds to a 0.09% increase in productivity at the plot-level (Model 2). These findings are consistent with our expectations, based on the literature, which finds that the adoption of modern agricultural inputs enhances productivity (Gollin et al., 2021).

Our results also show that households that apply pesticides on their plot are expected to have higher plot-level yields (Model 2). This is consistent with the literature, where pesticides are associated with a positive effect on yield growth (Fernandez-Cornejo et al., 1998). This effect is expected as pesticides are widely used in agriculture in order to prevent yield losses caused by pests, weeds, and diseases.

Further, we find that irrigation plays a significant role in plot-level productivity, exhibiting a positive effect. This finding aligns with existing literature, which highlights that irrigation can improve crop yields by enabling crops to use increased input applications better (Global Agricultural Productivity Initiative, 2020). In contrast, the estimated effects of organic fertilizer use and intercropping are not statistically significant. This is worth mentioning, as these practices are often expected to improve productivity by enhancing soil fertility.

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[2] These are not presented for brevity and they are included only as controls.

We also find that labor inputs are associated with higher yields at the plot-level.[3] This may reflect improved farm management practices or suggest that more intensive and timely operations contribute to higher productivity. We find that the estimated effects of agricultural inputs and irrigation are robust across different levels of aggregation at the household- (Model 3 and 4), plot manager- (Model 5), and cluster-level (Model 6), as shown in Table 4.2.[4]

4.2.2 Household Variables

We next examine how household characteristics affect agricultural productivity. Household size is associated with a decrease on yield. This is somewhat contrary to expectations, particularly given that increased labor increases capacity on-farm (Benjamin, 1992). So, we can interpret this in several ways. First, while larger households may have more labor available, this does not necessarily translate into higher productivity, as it can lead to inefficient labor allocation or include members who are not productive farmers, such as children. Second, because the majority of smallholder crop producers rely on agriculture for their livelihoods, larger households may face resource constraints and higher consumption needs, which in turn can limit investment in modern agricultural inputs and technologies, and reduce agricultural productivity.

We also see that experiencing a negative shock within the last 12 months is associated with negative impact on yields, which is expected from the literature (Josephson and Shively, 2021). Such events may reduce household capacity due to emotional distress, limit labor, and take resources away from farming, as households often shift their attention to immediate needs. It may also be that labor or resources are lost, if the shock represents the death of a productive member of the family in agriculture or earning wages outside of agriculture. These findings are consistent across models.

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[3] Appendix B.1 presents robustness checks in which total labor days are disaggregated into hired and family labor.

[4] Weather-related metrics and other controls are included in the analysis, but not shown in the table. Appendix B.2 provides robustness checks that assess the impact of including and excluding agro-ecological zone controls.

Table 4.2: Regression Results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Annual Time Trend	0.0003	-0.0197***	0.0062	-0.0038	-0.0080	-0.0132
	(0.0070)	(0.0065)	(0.0060)	(0.0086)	(0.0111)	(0.0213)
Log Fertilizer Value		0.0975***	0.0457***	0.0687***	0.0650***	0.0765***
		(0.0107)	(0.0075)	(0.0105)	(0.0105)	(0.0171)
Log Seed Value		0.1687***	0.1213***	0.0833***	0.0793***	0.0756***
		(0.0120)	(0.0109)	(0.0139)	(0.0165)	(0.0274)
Log Total Labor Days		0.3480***	0.4392***	0.4543***	0.4572***	0.5134***
		(0.0157)	(0.0149)	(0.0176)	(0.0193)	(0.0369)
Pesticide Use (Yes/No)		0.3047***	0.2858***	0.1197**	0.1405**	0.2107
		(0.0443)	(0.0377)	(0.0555)	(0.0598)	(0.1841)
Organic Fertilizer (Yes/No)		-0.0297	0.0194	-0.0810*	-0.0807*	-0.1909
		(0.0386)	(0.0329)	(0.0418)	(0.0450)	(0.1538)
Irrigated (Yes/No)		0.3283*	0.3068***	0.3887***	0.3134***	1.5263***
		(0.1742)	(0.0769)	(0.1133)	(0.1000)	(0.4800)
Intercropped (Yes/No)		-0.5282***	-0.0049	-0.0454	-0.0372	0.0016
		(0.0383)	(0.0497)	(0.0570)	(0.0596)	(0.1677)
Household Size		-0.0247***	-0.0244***	-0.0446***	-0.0526***	-0.1035***
		(0.0042)	(0.0046)	(0.0102)	(0.0132)	(0.0303)
Household Shock		-0.1369***	-0.1292***	-0.1023**	-0.1096***	-0.1747
		(0.0333)	(0.0342)	(0.0415)	(0.0413)	(0.1130)
Household Electricity Access		0.1074**	0.0897**	0.0686	0.0762	-0.0289
		(0.0466)	(0.0429)	(0.0630)	(0.0710)	(0.1868)
Farm Size		-0.0004	-0.0002**	-0.0002	-0.0071	0.0001
		(0.0003)	(0.0001)	(0.0043)	(0.0088)	(0.0008)
Number of Plots		-0.0051	0.0317***	0.0139*	0.0108	0.0062**
		(0.0043)	(0.0043)	(0.0075)	(0.0074)	(0.0027)
Is the plot manager a female? (Yes/No)		-0.2673***	-0.2782***	-0.1261**	0.1282	-0.4333*
		(0.0328)	(0.0298)	(0.0591)	(0.3430)	(0.2249)
Manager Age		-0.0050***	-0.0039***	-0.0082***	-0.0128***	-0.0165*
		(0.0009)	(0.0008)	(0.0026)	(0.0050)	(0.0089)
Manager Formal Education (Yes/No)		-0.0744**	-0.0569*	-0.0528	-0.0707	0.0754
		(0.0322)	(0.0297)	(0.0450)	(0.0491)	(0.1416)
Observations	221847	160779	45682	41939	44657	8366
R^2	0.108	0.355	0.503	0.818	0.844	0.882

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Additionally, we find that some household characteristics are only significant in the household-level Model 3 and do not have a significant effect at other levels of aggregation. We find that farm size and the number of plots held by a household are statistically significant, with negative and positive coefficients, respectively. Results from Model 3 suggest that households managing a greater number of plots are associated with higher yields. This positive effect may reflect greater flexibility in plot management, which can enable crop diversification, allowing farmers to reduce risk and stabilize income.

In contrast, larger farms often require more inputs and attention, and without the proper care or resources, this can lead to inefficiencies in productivity. This finding aligns with Jayne and Sanchez (2021), who documented that much of SSA's agricultural growth has come from expanding farmland rather than improving yields. These household characteristics, farm size and number of plots, are not significant at any other level of aggregation, including Model 4 with household fixed effects, which is consistent with expectations, as this specification controls for household characteristics that are unobserved and demonstrate minimal variation over time, which is the case for both farm size and the number of plots held by the household.

4.2.3 Plot Manager Variables

We last explore the estimated effect of plot manager characteristics on productivity outcomes. Table 4.2 shows that women managers and older individuals are associated with lower yields. These findings are consistent with existing literature, which indicates that women-managed plots tend to be less productive than those managed by men (Kilic et al., 2015; Slavchevska, 2015; Oseni et al., 2015; Aguilar et al., 2015). The negative coefficient associated with age is somewhat surprising, as we generally expect older farmers to have greater experience and thus to have greater productivity. However, increased age may reflect decline in physical capacity, as well as potential resource constraints faced by older individuals who may be past their prime earning years. These factors could jointly contribute to lower productivity outcomes.

Further, we find that plot managers with any formal education have lower plot yields. This finding is somewhat unexpected, as formal education is often linked to improved decision-making and productivity through knowledge about agriculture gained in school and/or increased access and knowledge of services associated with agriculture, such as extension services. However, this may not hold in the context of smallholder farming. One possible explanation is that the definition of formal education in our data is broad, often limited to completion of lower levels of formal education, and may not include content relevant to agriculture. Thus, the education received may not equip managers with the skills needed to improve agricultural productivity and may just measure interaction with school at some point in a person's life, rather than actual skill or experience gained in the classroom.

We find that the associated coefficients of plot manager traits are robust at both the plot- and household-level. However, in Model 5, which includes plot manager fixed effects to control for variation across managers, only age remains significant. This is expected, as gender and education typically do not vary over time, whereas age naturally increases.

4.3 Comparison with Wollburg et al. (2024)

One unexpected element of our work is the diversion between our findings that those of Wollburg et al. (2024). As we are using a dataset constructed by Bentze and Wollburg (2024) and following the Wollburg et al. (2024) analysis method, we anticipate similarities between our conclusions. Wollburg et al. (2024) find no evidence of improvement in smallholder crop productivity over the 12-year period covered in their study. They test multiple specifications across different levels of aggregation, following the same structure and control strategy described in Section 3. They find no evidence of productivity growth over time. In fact, five out of six specifications produce statistically significant negative trends, indicating a consistent decline in productivity. In this section, we compare our findings with those of Wollburg et al. (2024) to assess and try to understand observed differences. Specifically, we discuss two differences which may explain the divergence between our conclusions and those of Wollburg et al. (2024).

4.3.1 Household Data

One potential difference we consider is that while our data both come from the LSMS-ISA, the actual households and variables included, and thus the resultant dataset, are not the exactly same. This results in differences in both data coverage and variable construction.

First, there are differences in the data included. We include waves and crops which are omitted from Wollburg et al. (2024). In particular, we include an additional survey wave for Ethiopia (Wave 5).[5] We also account for two additional crop categories (fruits and cash crops), as we consider these to be important groups commonly grown in SSA.[6]

Another difference in the data included is related the measurement of data on seed. Measurement of some variables shifted across waves. This is the case for seed data in Tanzania in Waves 1 and 2, where only the amount spent on seeds was recorded, but not the quantity purchased in kilograms. We discuss this further in Section 2.1. The measurement of purchase value without weight prevents us from calculating seed value at constant prices, as doing so requires dividing the input value by quantity. Wollburg et al. (2024) addresses this issue by using the reported seed values deflated to 2020 USD. In contrast, we impute seed values for these observations using constant-price seed values from other waves in Tanzania as a reference.[7]

We also exclude a number of variables which are included by Wollburg et al. (2024). These include certain geospatial variables, such as soil fertility index and elevation, as they are missing for entire waves in some countries in our dataset. Their omission in our dataset impacts LASSO selection and ultimately results in the exclusion of those waves in our analysis. Thus, we omit those variables with missing data from our final analysis. Further, we do not include several variables including distance to road and distance to market, as they were not available in Bentze and Wollburg (2024) and so we omit them. Lastly, unlike Wollburg et al. (2024), we exclude the plot size from our main specification but present an alternative analysis including it in Appendix B.1.

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[5] The exclusion of Ethiopia wave 5 leads to results consistent with our findings. See Appendix B.1

[6] The inclusion or exclusion of these crop categories however, has no significant effect on results, whether the analysis considers only staple crops or staple crops, fruits, and cash crops results in the same results.

[7] As shown in Appendix B.1, using imputed constant-price seed values in Waves 1 and 2 in Tanzania or using reported seed values for those waves does not significantly affect our results.

LASSO selection itself is another way in which our analyses differ, because of the variables included in the initial selection pool. As LASSO is a data-driven method that selects variables based on their predictive power, we do not control which specific variables are chosen. Thus, with a different pool of variables between analyses, we will, by construction, end up with distinct selected variables, even if the data used to build them come from the same sources.

Finally, related to the dataset, there are differences in the measurement of variables within the data and their cleaning. Specifically, we differ in how input and output variables are cleaned in our analyses. In our analysis, we impute missing values and the top 5%, while retaining the bottom 5% to account for real zeros, as described in Section 2.1. Appendix B.1 presents a robustness check in which missing values are left as missing and only the top 5% are imputed. This alternative approach leads to results consistent with our main findings. In contrast, Wollburg et al. (2024) winsorize inputs and outputs at the 99th percentile in their main analysis. However, their results remain consistent across robustness checks using alternative methods to handle outliers and missing values, such as winsorizing harvest values at the 95th percentile, trimming or replacing harvest values per hectare with the median at both the 95th and 99th percentiles.

4.3.2 Weight adjustments

The next potential difference we consider are adjustments the population weights. While we use the same survey weights, which are created and distributed with the LSMS-ISA surveys, the adjustments to these weights differ slightly between our paper and Wollburg et al. (2024).

In both papers, household weights are adjusted to ensure that estimates are representative for the country. As described in Chapter 3, we adjust weights based on the level of aggregation to prevent households to adjust for that level and to prevent households from being “double counted”. Specifically, we divide household weights by the number of plots or number of plot managers within each household for Models at the plot- (Model 1 and 2) and plot manager-level (Model 5), respectively. For Model 6 at the cluster-level, we sum all household weights within each cluster. At the household-level (Models 3 and 4), we use the original household weights without adjustment.[8] Wollburg et al. (2024) follow a similar approach by dividing household weights by the number of plots within each household to avoid "double counting" of households with multiple plots. In addition, they rescale the weights so that they sum to the wave-specific target population and calibrate them to reflect the omission of nonagricultural households. We tried adjusting household weights the same way as Wollburg et al. (2024). However, after rescaling and calibrating the household weights, we were forced to drop observations that are no longer representative. This leads to the loss of several survey waves from our analysis. The results from this analysis are presented in Appendix B.2

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[8] We also conduct alternative analysis using different weighting methods, which are presented in Appendix B.2.

Chapter 5

Conclusion

Despite sustained investment in agricultural technologies and innovations, our analysis finds no evidence of statistically significant improvements in agricultural productivity across six Sub-Saharan African countries between 2008 and 2021. Using detailed LSMS-ISA data, we examine productivity at multiple levels of aggregation (plot, household, plot manager, and cluster) and consistently observe stagnant or declining yields over time. Even when evaluating trends disaggregated by country, individual patterns vary, but we find no consistent evidence of regional yield growth. This lack of improvement raises critical questions about the efficacy of current agricultural development strategies in the region.

To better understand these persistent trends, we explore a set of factors associated with productivity at each level. We find that agricultural inputs, such as fertilizer, seed, and labor, are positively associated with yields. However, household characteristics and plot manager traits, including gender and education, are often negatively correlated with productivity. These counteracting associations may help explain the broader stagnation of yields across the region, suggesting that gains from input use may be offset by underlying structural and demographic constraints.

By estimating six regression models at varying levels of aggregation, this study highlights the importance of disaggregated analysis in unpacking and understanding agricultural performance. Productivity challenges are often rooted at the plot-level and may not be fully visible or adequately captured in more aggregated data. Our findings underscore that input-focused interventions, though necessary, are insufficient on their own. Complementary policies that target managerial and household-level barriers, including gender-based disparities, access considerations, education gaps, program targeting, and labor shortages, are essential for translating input use into sustained and ongoing productivity gains.

Ultimately, with this paper, we contribute to a deeper understanding of the factors that constrain agricultural productivity growth among smallholder farmers in Sub-Saharan Africa. In doing so, we offer insight for shaping more effective and inclusive agricultural policies that can support improved livelihoods and foster food security throughout the region.

Appendix A

Weather

A.1 Weather Data

In this section, we describe the weather metrics used in the analysis and outline the methodology used to select them. We also compare the EO sources from which the data are drawn.

We use rainfall data from three EO sources. While these products provide the same set of rainfall metrics, they differ in modeling approaches, input sources, and spatial resolutions. Figure A.1 shows an example of how rainfall metrics differ across products. The figure shows the different distributions of total seasonal rainfall across EO products. We use The Climate Hazards group InfraRed Precipitation with Station Data (CHIRPS), ERA5, and Climate Prediction Center (CPC) Unified Gauge-Based Analysis of Daily Precipitation and Temperature. In our primary results, we rely on CHIRPS rainfall data due to its modeling approach and coverage and ERA5 for all temperature-related metrics.

Details about each product are summarized below:

- CHIRPS integrates gauge-based observations with meteorological satellite data, where gauge data provide site-level observations, and the satellite data provide a broader spatial coverage (Funk et al., 2015).

- ERA5 is produced by the European Centre for Medium-Range Weather Forecasts. It combines data from satellites, weather stations, ships, and aircraft using assimilation models to simulate the Earth's climate or specific weather events (Hennermann and Berrisford, 2020).

- CPC relies solely on station-based observations, uses spatial interpolation techniques to produce a complete precipitation map from measured data (Chen et al., 2008).

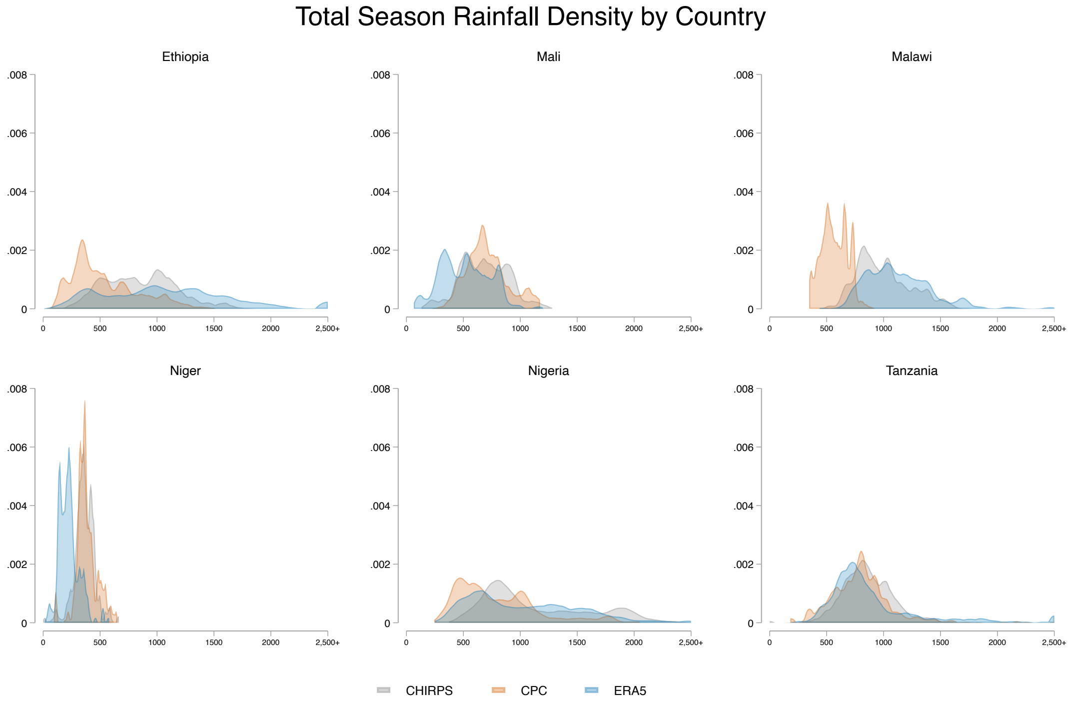

Figure A.1: Total season rainfall density by country.

We use LASSO (Least Absolute Shrinkage and Selection Operator) to determine which weather metrics are used in our regression models. This method allows us to select the most relevant predictors from a larger pool of weather variables. The list of potential variables includes rainfall metrics from CHIRPS, ERA5, or CPC, paired with temperature variables from ERA5.[1] We test all three weather datasets, but ultimately only use CHIRPS rainfall data, paired with ERA5 temperature data in the final analysis of this paper. Results using ERA5 and CPC metrics are included in Appendix A for comparison. Table A.1 summarizes which rainfall and temperature metrics are selected by LASSO for each EO product. A checkmark (✓) indicates that the variable was selected for inclusion in our specifications. It is worth noting that among the full set of weather metrics, only no rain days and maximum daily temperature are consistently selected by LASSO across all three products.

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[1] We use ERA5 temperature metrics for consistency, since temperature data from CHIRPS and CPC contain missing values that affect LASSO selection.

Table A.1: LASSO Selection Results: Weather Metrics by Product.

Variable	**CHIRPS**	**ERA5**	**CPC**
Rainfall			
– Mean Daily Rainfall	○	○	○
– Median Daily Rainfall	○	○	○
– Variance of Daily Rainfall	○	✓	○
– Skew of Daily Rainfall	○	✓	✓
– Total Rainfall	○	○	○
– Deviation in Total Rainfall	○	○	✓
– Z-score of Total Rainfall	○	✓	✓
– Rainy Days	○	○	○
– Deviation in Rainy Days	○	○	○
– No Rain Days	✓	✓	✓
– Deviation in No Rain Days	○	○	○
– Percent Rainy Days	○	○	○
– Deviation in Percent Rainy Days	○	○	○
– Longest Dry Spell	○	○	○
Temperature			
– Mean Daily Temperature	○	○	○
– Median Daily Temperature	○	○	○
– Variance of Daily Temperature	○	○	○
– Skew of Daily Temperature	✓	✓	✓
– Growing Degree Days (GDD)	○	○	○
– Deviation in GDD	○	○	○
– Z-score of GDD	○	○	○
– Maximum Daily Temperature	✓	○	✓
– Temperature Bin 0-20	○	○	○
– Temperature Bin 20-40	○	○	○
– Temperature Bin 40-60	○	○	○
– Temperature Bin 60-80	○	○	○
– Temperature Bin 80-100	○	○	○

A.2 Results by Weather Source

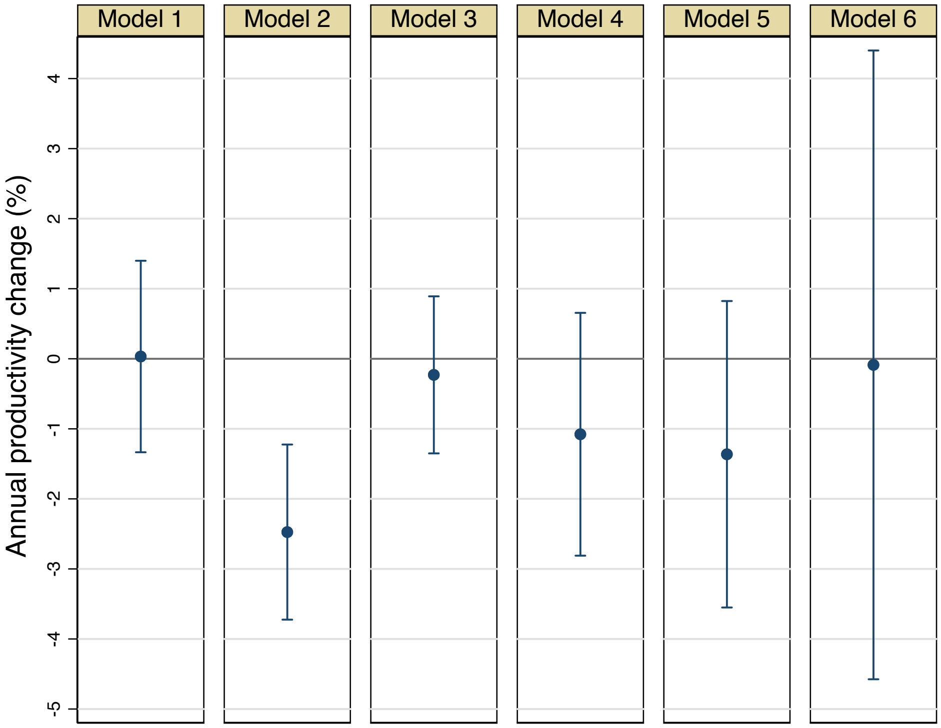

Figure A.2: Annual productivity estimated coefficients - CPC

Table A.2: Regression Results - CPC

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Annual Time Trend	0.0003	-0.0247***	-0.0023	-0.0108	-0.0136	-0.0009
	(0.0070)	(0.0064)	(0.0057)	(0.0088)	(0.0112)	(0.0229)
Log Fertilizer Value		0.0995***	0.0501***	0.0683***	0.0639***	0.0735***
		(0.0106)	(0.0076)	(0.0104)	(0.0104)	(0.0171)
Log Seed Value		0.1692***	0.1273***	0.0817***	0.0771***	0.0659**
		(0.0118)	(0.0107)	(0.0137)	(0.0164)	(0.0276)
Log Total Labor Days		0.3523***	0.4385***	0.4489***	0.4533***	0.4971***
		(0.0158)	(0.0145)	(0.0169)	(0.0190)	(0.0368)
Pesticide Use (Yes/No)		0.2934***	0.2807***	0.1323**	0.1543***	0.2360
		(0.0437)	(0.0366)	(0.0533)	(0.0593)	(0.1844)
Organic Fertilizer (Yes/No)		-0.0209	0.0402	-0.0933**	-0.0968**	-0.2833*
		(0.0384)	(0.0330)	(0.0408)	(0.0442)	(0.1510)
Irrigated (Yes/No)		0.3322*	0.3235***	0.3924***	0.3111***	1.4883***
		(0.1745)	(0.0778)	(0.1116)	(0.0989)	(0.4919)
Intercropped (Yes/No)		-0.5116***	0.0251	-0.0344	-0.0242	-0.0455
		(0.0376)	(0.0486)	(0.0567)	(0.0592)	(0.1607)
Household Size		-0.0249***	-0.0257***	-0.0428***	-0.0505***	-0.0906***
		(0.0042)	(0.0045)	(0.0103)	(0.0133)	(0.0286)
Household Shock		-0.1417***	-0.1251***	-0.0786*	-0.0896**	-0.0121
		(0.0333)	(0.0340)	(0.0409)	(0.0411)	(0.1141)
Household Electricity Access		0.1072**	0.0892**	0.0698	0.0872	0.0471
		(0.0460)	(0.0424)	(0.0625)	(0.0705)	(0.2052)
Farm Size		-0.0004	-0.0002***	-0.0002	-0.0073	0.0000
		(0.0003)	(0.0001)	(0.0045)	(0.0091)	(0.0008)
Number of Plots		-0.0049	0.0338***	0.0206***	0.0171**	0.0055**
		(0.0043)	(0.0043)	(0.0071)	(0.0070)	(0.0023)
Is the plot manager a female? (Yes/No)		-0.2530***	-0.2568***	-0.1388**	0.1362	-0.4958**
		(0.0323)	(0.0290)	(0.0599)	(0.3363)	(0.2200)
Manager Age		-0.0049***	-0.0033***	-0.0071***	-0.0120**	-0.0120
		(0.0009)	(0.0008)	(0.0026)	(0.0050)	(0.0095)
Manager Formal Education (Yes/No)		-0.0739**	-0.0523*	-0.0347	-0.0437	0.1005
		(0.0325)	(0.0296)	(0.0445)	(0.0490)	(0.1417)
Observations	221847	160779	45682	41939	44657	8366
R^2	0.108	0.357	0.509	0.821	0.847	0.886

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

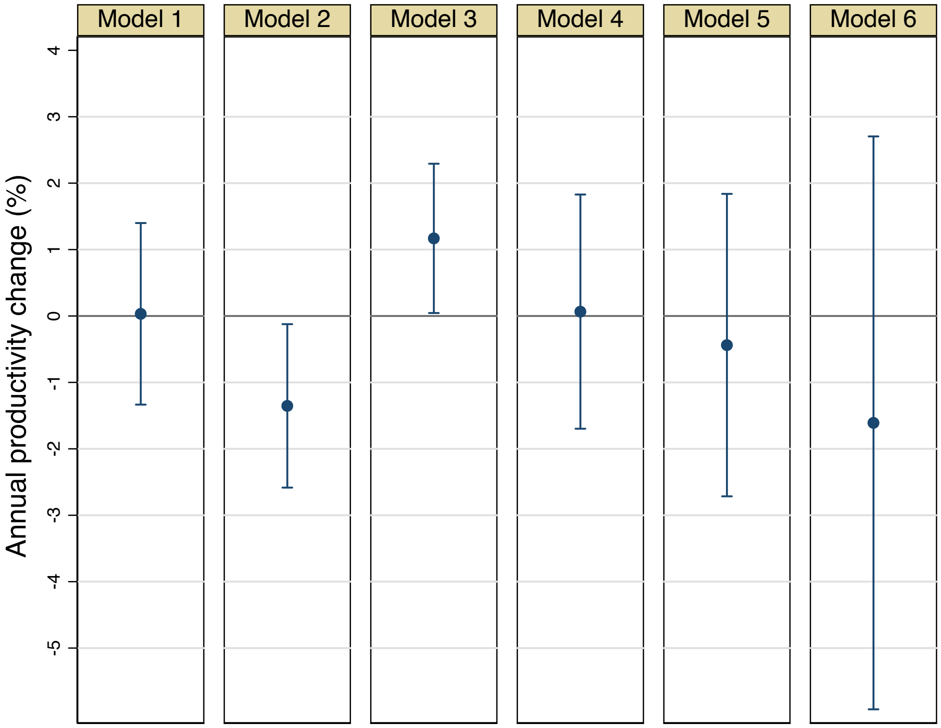

Figure A.3: Annual productivity estimated coefficients - ERA5

Table A.3: Regression Results - ERA5

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Annual Time Trend	0.0003	-0.0135**	0.0117**	0.0007	-0.0044	-0.0161
	(0.0070)	(0.0063)	(0.0057)	(0.0090)	(0.0116)	(0.0220)
Log Fertilizer Value		0.1020***	0.0520***	0.0694***	0.0660***	0.0816***
		(0.0107)	(0.0072)	(0.0107)	(0.0106)	(0.0186)
Log Seed Value		0.1728***	0.1224***	0.0840***	0.0797***	0.0735**
		(0.0118)	(0.0107)	(0.0140)	(0.0168)	(0.0289)
Log Total Labor Days		0.3426***	0.4360***	0.4428***	0.4472***	0.4902***
		(0.0145)	(0.0144)	(0.0181)	(0.0196)	(0.0392)
Pesticide Use (Yes/No)		0.2963***	0.2784***	0.1319**	0.1532**	0.2906
		(0.0446)	(0.0375)	(0.0563)	(0.0601)	(0.1854)
Organic Fertilizer (Yes/No)		-0.0251	0.0204	-0.0530	-0.0531	0.0008
		(0.0375)	(0.0326)	(0.0416)	(0.0439)	(0.1492)
Irrigated (Yes/No)		0.3484*	0.3243***	0.3952***	0.3189***	1.6416***
		(0.1813)	(0.0800)	(0.1153)	(0.0995)	(0.4971)
Intercropped (Yes/No)		-0.5325***	-0.0060	-0.0343	-0.0278	0.0162
		(0.0386)	(0.0499)	(0.0575)	(0.0596)	(0.1721)
Household Size		-0.0228***	-0.0222***	-0.0492***	-0.0576***	-0.1259***
		(0.0042)	(0.0046)	(0.0103)	(0.0133)	(0.0292)
Household Shock		-0.1287***	-0.1194***	-0.1129***	-0.1234***	-0.2257*
		(0.0330)	(0.0339)	(0.0420)	(0.0421)	(0.1220)
Household Electricity Access		0.1057**	0.0899**	0.0497	0.0521	-0.0766
		(0.0463)	(0.0430)	(0.0628)	(0.0700)	(0.1920)
Farm Size		-0.0004	-0.0002**	-0.0002	-0.0074	-0.0001
		(0.0003)	(0.0001)	(0.0045)	(0.0090)	(0.0008)
Number of Plots		-0.0057	0.0313***	0.0153**	0.0121	0.0068**
		(0.0041)	(0.0042)	(0.0076)	(0.0076)	(0.0029)
Is the plot manager a female? (Yes/No)		-0.2668***	-0.2759***	-0.1225**	0.1238	-0.4185*
		(0.0327)	(0.0297)	(0.0594)	(0.3396)	(0.2307)
Manager Age		-0.0051***	-0.0041***	-0.0085***	-0.0137***	-0.0207**
		(0.0009)	(0.0008)	(0.0026)	(0.0050)	(0.0086)
Manager Formal Education (Yes/No)		-0.0948***	-0.0755**	-0.0567	-0.0732	-0.0014
		(0.0320)	(0.0294)	(0.0458)	(0.0512)	(0.1339)
Observations	221847	160779	45682	41939	44657	8366
R^2	0.108	0.359	0.506	0.817	0.844	0.880

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B

Robustness Checks

B.1 Data

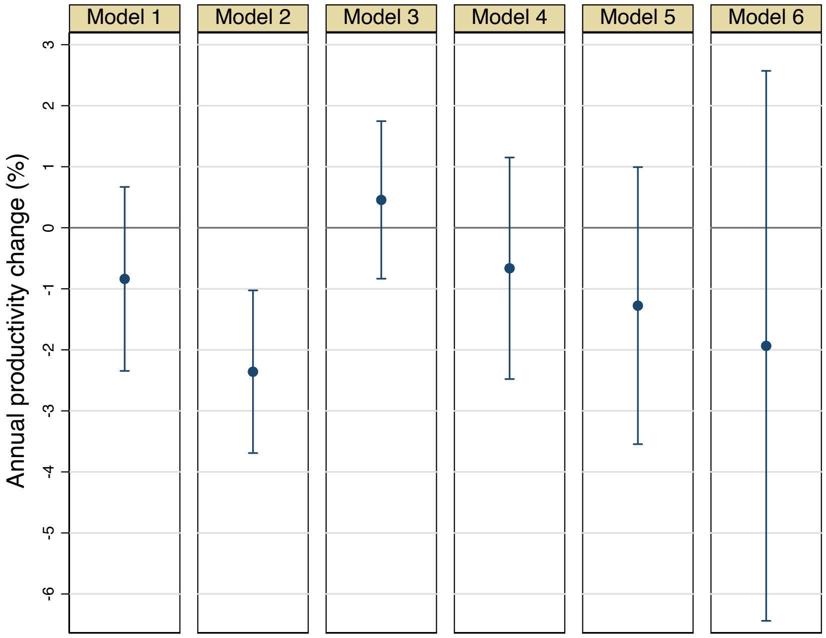

Figure B.2: Regression results using data in which only the top 5 % of agricultural input values are imputed, while missing values are left unchanged.

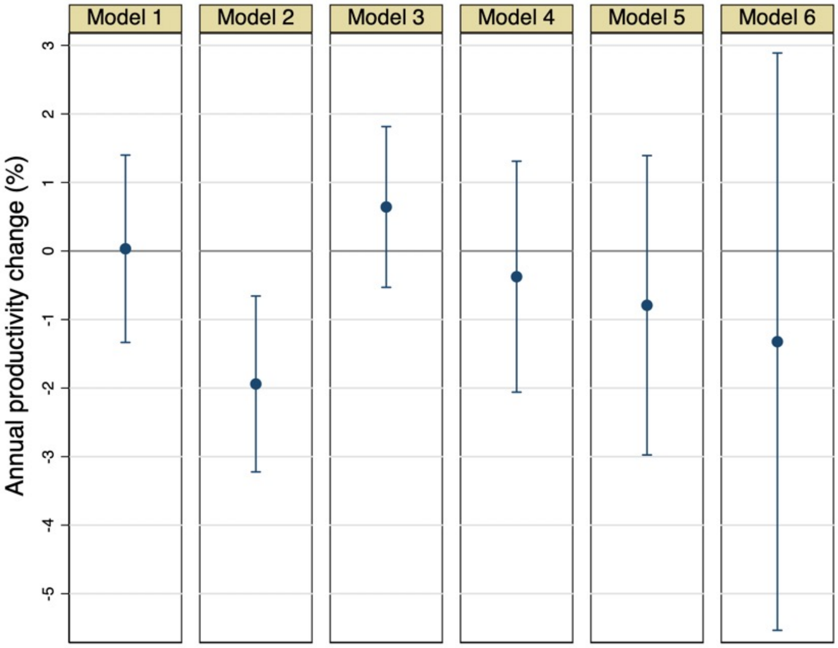

Figure B.1: Regression results using reported seed value deflated to 2020 USD for Tanzania Waves 1 and 2.

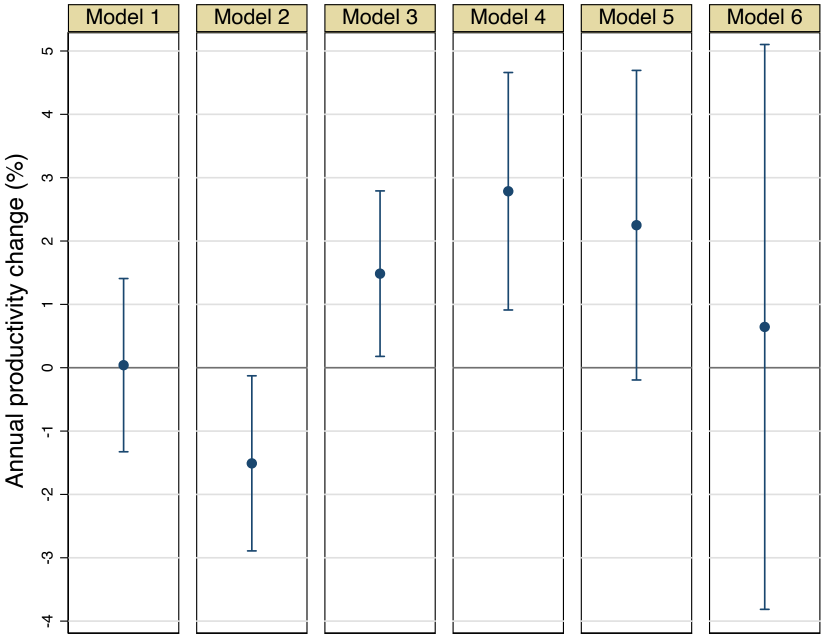

Figure B.3: Regression results disaggregating total labor into hired and family labor components.

Table B.1: Regression Results: Hired and Family Labor

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Annual Time Trend	0.0004	-0.0151**	0.0149**	0.0279***	0.0225*	0.0064
	(0.0070)	(0.0070)	(0.0067)	(0.0096)	(0.0125)	(0.0224)
Log Fertilizer Value		0.1343***	0.0767***	0.1071***	0.1028***	0.1101***
		(0.0116)	(0.0083)	(0.0127)	(0.0126)	(0.0227)
Log Seed Value		0.2656***	0.2368***	0.2028***	0.1945***	0.2617***
		(0.0124)	(0.0112)	(0.0158)	(0.0174)	(0.0367)
Log Hired Labor Days		0.0444***	0.0401***	-0.0081	-0.0051	-0.0039
		(0.0094)	(0.0073)	(0.0101)	(0.0099)	(0.0252)
Log Family Labor Days		0.0792***	0.1495***	0.1132***	0.1179***	0.1456**
		(0.0209)	(0.0199)	(0.0230)	(0.0251)	(0.0660)
Pesticide Use (Yes/No)		0.2720***	0.2328***	0.1252**	0.1460**	0.0817
		(0.0465)	(0.0393)	(0.0535)	(0.0604)	(0.2015)
Organic Fertilizer (Yes/No)		0.1381***	0.1504***	0.0431	0.0524	0.1118
		(0.0376)	(0.0344)	(0.0461)	(0.0476)	(0.1983)
Irrigated (Yes/No)		0.3235**	0.3345***	0.4036***	0.3218***	1.7561***
		(0.1472)	(0.0720)	(0.1016)	(0.1033)	(0.4430)
Intercropped (Yes/No)		-0.4607***	0.1667***	0.0241	0.0306	0.1239
		(0.0368)	(0.0484)	(0.0593)	(0.0698)	(0.1961)
Household Size		-0.0181***	-0.0232***	-0.0477***	-0.0527***	-0.1262***
		(0.0045)	(0.0051)	(0.0115)	(0.0137)	(0.0356)
Household Shock		-0.1312***	-0.1098***	-0.0996**	-0.1110**	-0.2867**
		(0.0333)	(0.0342)	(0.0415)	(0.0444)	(0.1267)
Household Electricity Access		0.0820*	0.0907**	0.0094	0.0159	-0.0843
		(0.0483)	(0.0459)	(0.0661)	(0.0767)	(0.2202)
Farm Size		-0.0008	-0.0004***	-0.0004	-0.0144	0.0000
		(0.0006)	(0.0002)	(0.0094)	(0.0180)	(0.0012)
Number of Plots		0.0013	0.0497***	0.0400***	0.0373***	0.0139***
		(0.0046)	(0.0051)	(0.0096)	(0.0095)	(0.0037)
Is the plot manager a female? (Yes/No)		-0.1826***	-0.1712***	-0.1015*	0.3010	-0.0942
		(0.0334)	(0.0316)	(0.0612)	(0.3034)	(0.2541)
Manager Age		-0.0038***	-0.0028***	-0.0077***	-0.0122**	-0.0172
		(0.0009)	(0.0009)	(0.0027)	(0.0051)	(0.0107)
Manager Formal Education (Yes/No)		-0.0227	0.0019	-0.0357	-0.0684	0.0765
		(0.0317)	(0.0298)	(0.0462)	(0.0517)	(0.1664)
Observations	221727	160711	45648	41905	44622	8357
R^2	0.108	0.314	0.431	0.788	0.820	0.855

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

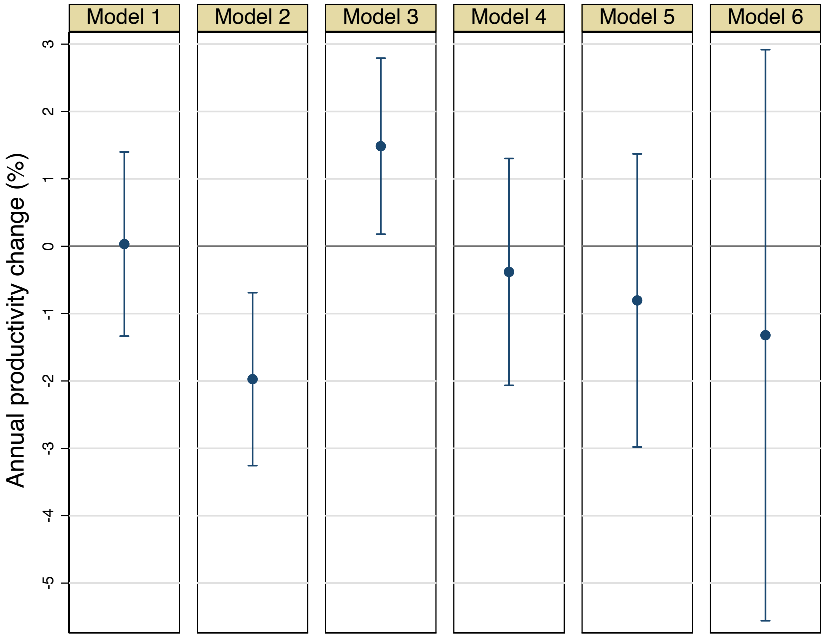

Figure B.4: Regression results including plot area as a variable.

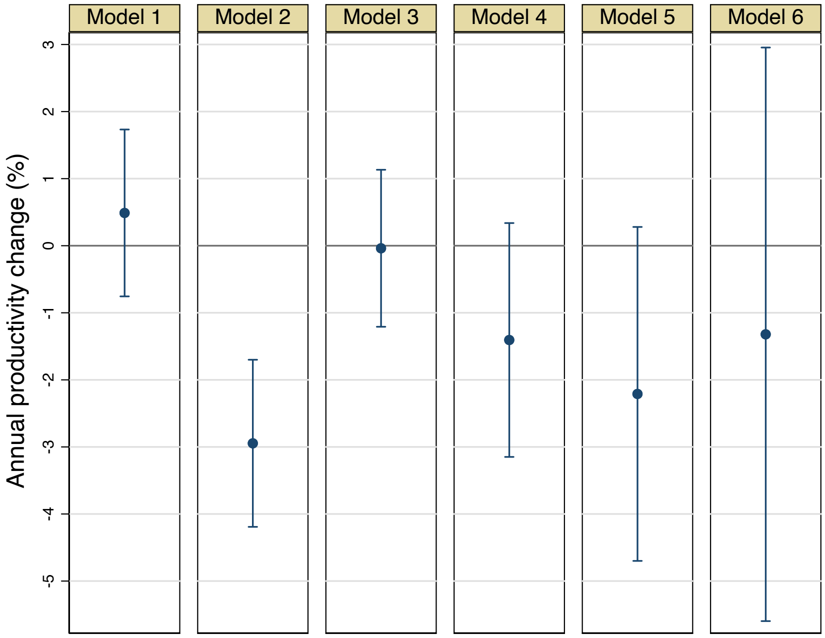

Figure B.5: Regression results excluding Ethiopia wave 5.

B.2 Weights and Controls

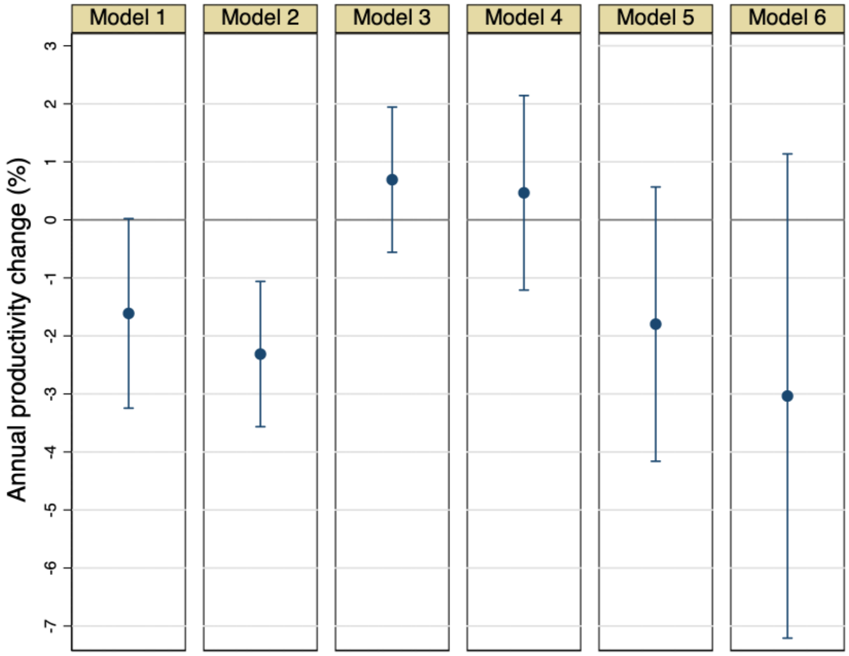

Figure B.6: Regression results after dropping non-representative observations.

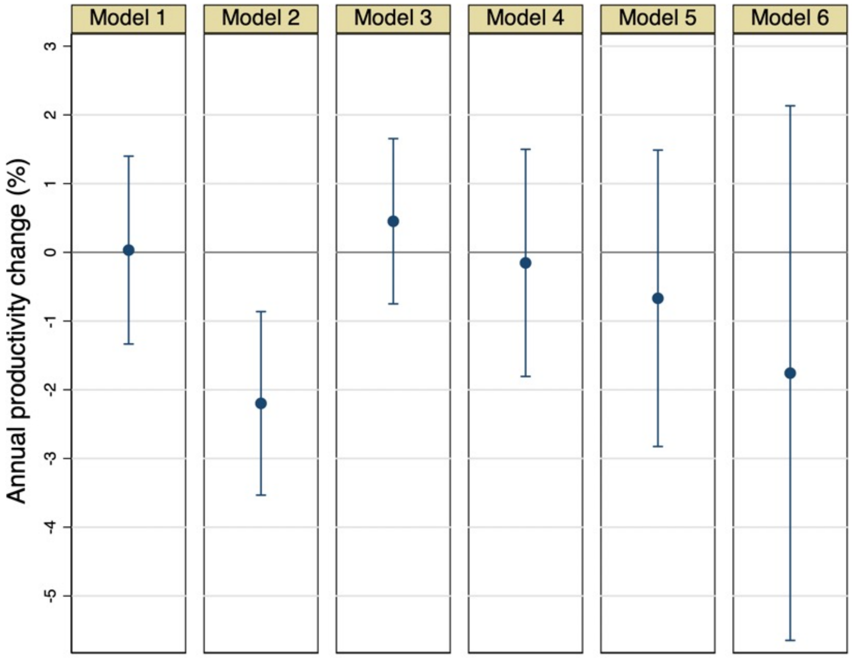

Figure B.7: Main analysis excluding agroecological zones.

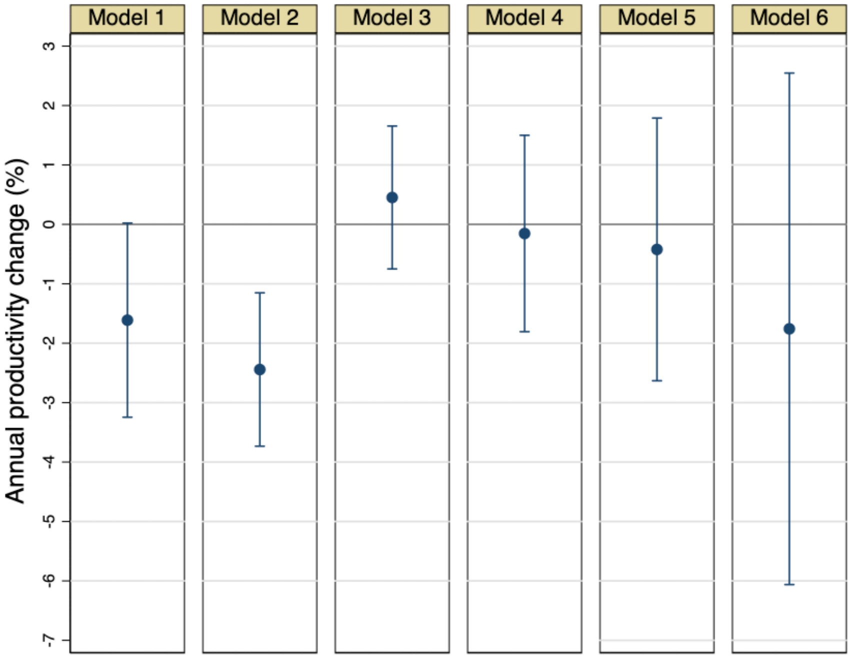

Figure B.8: Regression results using unadjusted weights excluding agroecological zones.

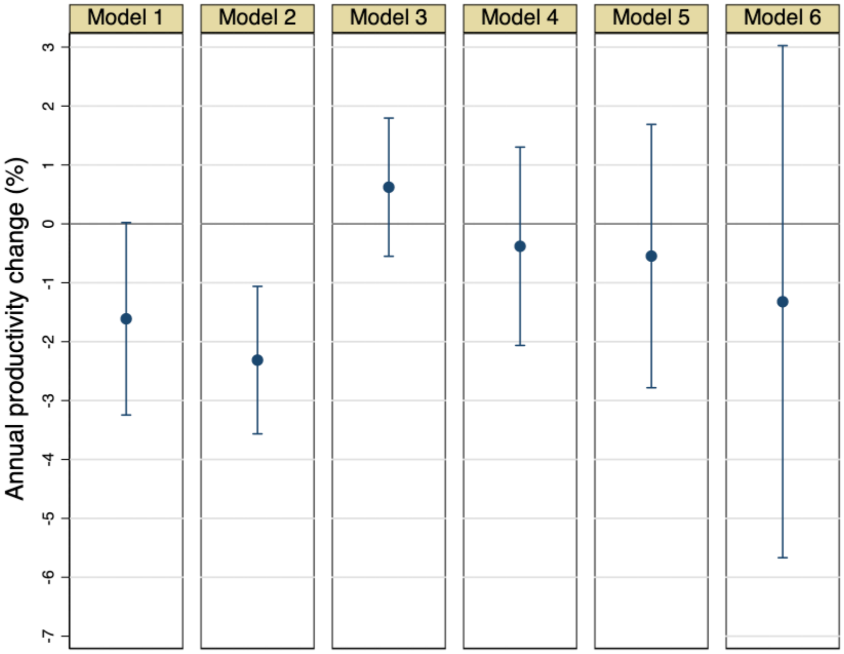

Figure B.9: Regression results using unadjusted weights including agroecological zones.

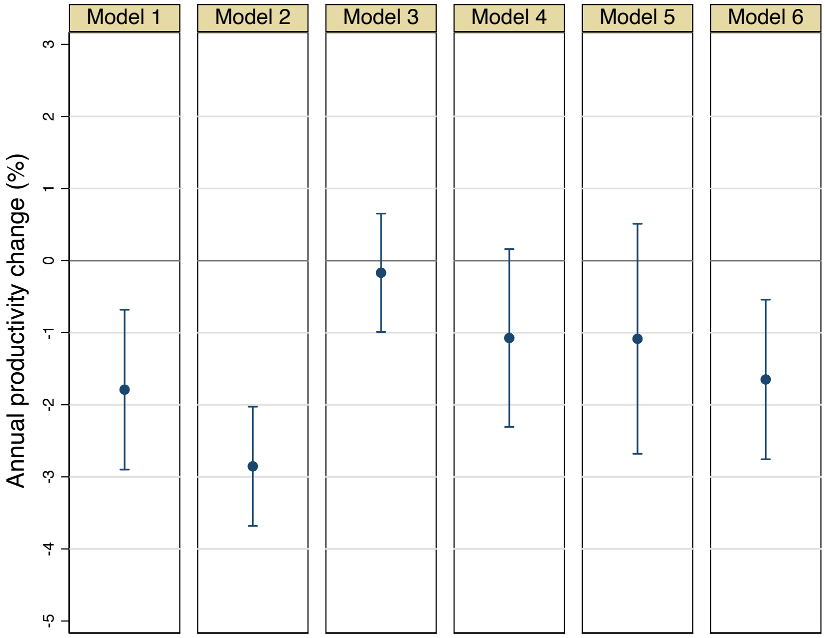

Figure B.10: Regression results without weights, excluding agroecological zones.

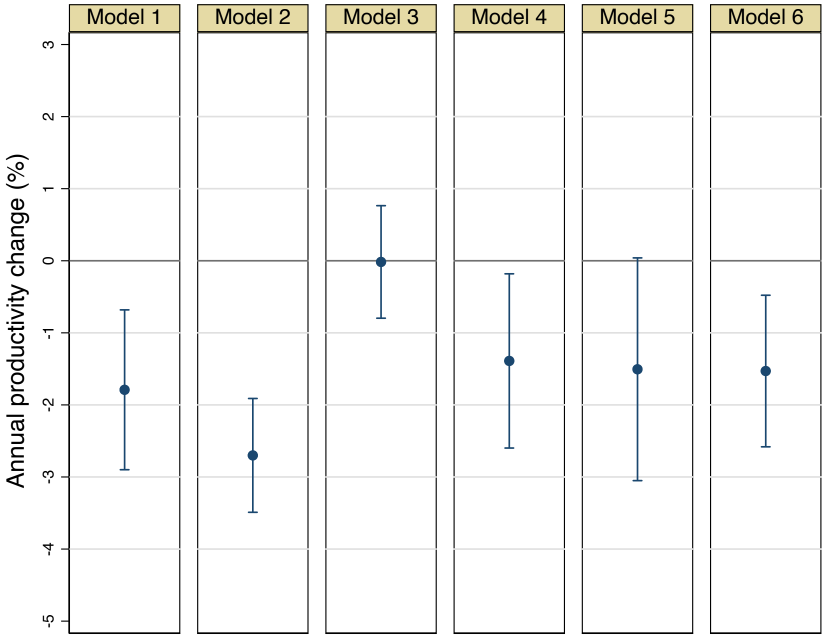

Figure B.11: Regression results without weights, including agroecological zones.

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