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Three Economic Essays on Climate Change Impacts and Adaptation in Africa's Agricultural Sector

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Abstract

How does climate change affect Africa's agricultural sector, and how do households and individuals respond to these challenges? This dissertation presents three empirical investigations of these fundamental questions, offering new evidence on both the impacts and the mechanisms through which households adapt. Drawing on rich microdata from Ethiopia and Tanzania, combined with satellite weather information, the studies uncover important insights about climate impacts and adaptation in Africa's agricultural sector.

The first essay demonstrates that rural households actively reshape their economic lives in response to drought shocks. Analyzing Ethiopian panel data, the study shows that both short-term and persistent droughts trigger a significant reallocation of labor from farming to off-farm self-employment — a shift that helps households smooth consumption and maintain food security. This adaptation is particularly pronounced among households with access to financial services, revealing how financial inclusion shapes adaptive capacity.

The second essay investigates how rising temperatures undermine agricultural productivity through resource misallocation, a previously undocumented but important impact channel. Using detailed plot–level crop farming data from Tanzania, the study provides new evidence that exposure to high temperatures above 30°C exacerbates distortions in land and capital allocation, reducing aggregate productivity. However, secure private property rights can substantially mitigate these temperature–induced inefficiencies, highlighting how institutional reforms in the land market can enhance resilience to the climate impacts.

The third essay establishes a causal link between human capital accumulation and climate change adaptation. Exploiting the expansion of education access due to the introduction of free primary education in Ethiopia, the study finds that additional years of formal education significantly increase the adoption of climate-resilient farming practices and technologies. These findings underscore the crucial role of human capital in the global response to climate change, particularly in low–income countries, by helping the most vulnerable to understand and address its impacts.

Collectively, this dissertation advances our understanding of the impacts of climate change and adaptation in Africa's agricultural sector, offering crucial evidence to design integrated policies that strengthen institutional frameworks, expand economic opportunities, and build human capital to enhance adaptation.

Zusammenfassung

Wie wirkt sich der Klimawandel auf den afrikanischen Agrarsektor aus und wie reagieren Haushalte und Einzelpersonen auf diese Herausforderungen? In dieser Dissertation werden drei empirische Untersuchungen zu diesen grundlegenden Fragen vorgestellt, die neue Erkenntnisse sowohl zu den Auswirkungen als auch zu den Anpassungsmechanismen der Haushalte liefern. Die Studien stützen sich auf umfangreiche Mikrodaten aus Äthiopien und Tansania, die mit Satellitenwetterdaten kombiniert wurden, und liefern drei wichtige Erkenntnisse über die Auswirkungen des Klimawandels und die Anpassung im afrikanischen Agrarsektor.

Das erste Essay zeigt, dass ländliche Haushalte ihr Wirtschaftsleben als Reaktion auf Dürreschocks aktiv umgestalten. Die Studie analysiert äthiopische Panel-Haushaltsdaten, die mit historischen Satellitenwetterdaten zusammengeführt werden, und kommt zu dem Ergebnis, dass sowohl kurzfristige als auch anhaltende Dürreperioden eine erhebliche Umschichtung von Arbeitskräften von der Landwirtschaft auf außerlandwirtschaftliche Selbstständigkeit auslösen - eine Verlagerung, die dazu beiträgt, den Verbrauch und die Ernährungssicherheit der Haushalte zu erhalten. Diese Anpassung ist bei Haushalten mit Zugang zu Finanzdienstleistungen besonders ausgeprägt und zeigt, wie der Marktzugang die Anpassungsfähigkeit beeinflusst.

Das zweite Essay zeigt, wie steigende Temperaturen die landwirtschaftliche Produktivität durch Fehlallokation von Ressourcen untergraben - ein bisher nicht dokumentierter, aber wichtiger Wirkungskanal. Anhand detaillierter Daten zum Ackerbau auf Parzellenebene in Tansania zeigt die Analyse, dass hohe Temperaturen von über 30°C die Verzerrungen bei der Land- und Kapitalallokation verstärken und die Gesamtproduktivität verringern. Sichere private Eigentumsrechte können diese temperaturbedingten Ineffizienzen jedoch erheblich abmildern und zeigen, wie institutionelle Reformen auf dem Landmarkt die Widerstandsfähigkeit gegenüber den Klimaauswirkungen erhöhen können.

Im dritten Essay wird ein kausaler Zusammenhang zwischen der Akkumulation von Humankapital und der Anpassung an den Klimawandel hergestellt. Unter Ausnutzung der Ausweitung des Bildungszugangs infolge der Einführung der kostenlosen Grundschulbildung in Äthiopien zeigt die Studie, dass zusätzliche Jahre formaler Schulbildung die Übernahme klimaresistenter landwirtschaftlicher Praktiken und Technologien deutlich erhöhen. Diese Ergebnisse unterstreichen die entscheidende Rolle des Humankapitals bei der globalen Reaktion auf den Klimawandel, insbesondere in Ländern mit niedrigem Einkommen, da es den am meisten gefährdeten Menschen hilft, die Auswirkungen des Klimawandels zu verstehen und zu bewältigen.

Insgesamt trägt diese Dissertation zu einem besseren Verständnis der Auswirkungen des Klimawandels und der Anpassung im afrikanischen Agrarsektor bei und liefert wichtige Erkenntnisse für die Entwicklung integrierter politischer Maßnahmen, die den institutionellen Rahmen stärken, wirtschaftliche Möglichkeiten erweitern und Humankapital aufbauen, um die Anpassung zu verbessern.

Contents

List of Figures

List of Tables

Introduction

Climate change represents one of the most pressing challenges of our time, with its impacts felt disproportionately across regions and populations (Hallegatte and Rozenberg, 2017; King and Harrington, 2018; Diffenbaugh and Burke, 2019). Africa is at the forefront of this crisis, facing threats that could fundamentally reshape its social and economic landscape. According to World Meteorological Organization (2024), the region faces an outsized economic burden from climate change, with countries losing 2–5 percent of their gross domestic product (GDP) and diverting up to 9 percent of national budgets to climate response measures. The financial strain is particularly acute in sub-Saharan Africa (SSA), where adaptation costs are projected to reach USD. 30–50 billion annually over the next decade — equivalent to 2–3 percent of regional GDP. The Intergovernmental Panel on Climate Change (IPCC) projects that temperature increases in Africa will exceed the global mean, with some regions expected to experience warming up to 1.5 times the global average (IPCC, 2022a). This accelerated warming is particularly concerning given Africa's limited adaptive capacity, widespread poverty, and heavy reliance on climate–sensitive economic activities.

The agricultural sector, which employs 65–70 percent of SSA's population and accounts for about 30–40 percent of GDP [1], faces acute vulnerability to climate change. Rising temperatures, shifting rainfall patterns, and the increasing frequency of extreme weather events pose existential threats to agricultural productivity and food security in the region. Recent evidence suggests that crop yields in Africa could decline by up to 30 percent by 2050 due to climate change (IPCC, 2022b), while the frequency of extreme weather events such as droughts has already doubled since 1990 (World Meteorological Organization, 2024). The combination of rising temperatures and rainfall variability particularly threatens rain–fed agriculture, which accounts for more than 95 percent of cropland in SSA (FAO, 2020).

These climate threats intersect with structural challenges in African agriculture — limited access to better technologies, incomplete input markets, weak institutions, and persistent poverty — creating a complex web of vulnerabilities. Experts from the World Bank estimate that without effective adaptation measures, climate change could push an additional 32–132 million people into extreme poverty by 2030 , with a significant proportion in SSA (Jafino et al., 2020) . This stark reality has elevated adaptation, resilience building, and mitigation of climate change to the forefront of development policy discourse. However, designing effective adaptation strategies requires a deep micro-level understanding of how individuals, households and firms respond to climate shocks, how existing institutions mediate these responses, and what role human capital development plays in fostering adaptive capacity.

This dissertation contributes to this crucial policy dialogue through three interconnected microeconomic essays examining different dimensions of climate change impacts and adaptation in Africa's agricultural sector. The research uses Ethiopia and Tanzania as representative case studies due to their high economic vulnerability (UNDESA, 2019) and notable educational and land institutional reforms, employs various

[1] World Bank Africa Development Indicators: `https://databank.worldbank.org/source/africa-development-indicators` and the ILO Database (ILOSTAT): `https://ilostat.ilo.org/data/`

novel microdata sets and deploys rigorous econometric methods, and analyzes impacts and different adaptation mechanisms — from household responses through rural labor markets to resource use efficiency, and the role of human capital development. Together, these essays provide novel insights into how African farming communities confront climate change and how they can build resilience against these crises.

The first essay investigates how rural households in Ethiopia adapt to drought shocks through labor reallocation between agricultural and non–agricultural sectors. Using three waves of panel data from the Living Standards Measurement Study–Integrated Surveys on Agriculture (LSMS–ISA) merged with geospatial weather datasets spanning 5 decades and exploiting spatio–temporal variations in drought exposure, the study examines the impacts of both short–term and persistent droughts on household labor reallocation decisions. The findings reveal that households reduce on–farm work and increase off–farm self–employment in response to droughts, without abandoning farming altogether. This diversification into off–farm activities, driven by drought–related productivity declines in agriculture, helps smooth consumption and protect households from food insecurity. Importantly, households with better access to financial services show greater capacity to reallocate labor to off–farm jobs, highlighting how financial inclusion can enhance adaptive capacity.

The most recent evidence shows that crop productivity in smallholder farming systems in SSA has declined by 3.5% annually over the past decade (Wollburg et al., 2024) which is partly attributed to the misallocation of production factors, largely driven by incomplete input markets and weak property rights (Restuccia et al., 2008; Gollin and Udry, 2021; Chen et al., 2023; Suri et al., 2024). Despite the evidence linking resource misallocation with reduced agricultural productivity in SSA, there remains limited understanding of how the changing climate amplifies these allocative inefficiencies. Against this background, the second essay examines how rising temperatures exacerbate resource misallocation in Tanzania's agricultural sector and explores the potential role of secure property rights in alleviating these distortions. Combining detailed plot–level data from LSMS–ISA with satellite weather information, the study employs fixed effects panel regressions that exploit exogenous variation in daily average temperature during the growing season. The results show that increased exposure to temperatures above 30°C significantly contributes to higher aggregate misallocation, primarily driven by distortions in land and capital use. Crucially, the study provides evidence that secure private property rights to land can help mitigate this temperature–driven misallocation, emphasizing the role of institutional reforms in building resilience.

Drawing on the sharp rise in education rates in SSA over the last three decades (World Bank and UNICEF, 2008) — the same period in which the frequency of extreme weather events in SSA has doubled (World Meteorological Organization, 2024) — the third essay investigates the role of human capital accumulation in shaping climate change beliefs and its impacts on on-farm adaptation in Ethiopia. Exploiting variation in age-cohort exposure to the potential regional impact of free primary education (FPE) — a policy reform that was introduced in 1995 — as a natural experiment and a plausibly valid instrument for schooling years, the study employs an instrumental variable (IV) empirical framework to estimate the causal effects of formal education attainment on adoption of climate-smart agriculture (CSA). These technologies are crucial to transform and reorganize agriculture in the new realities of climate change to sustainably increase productivity, improve adaptation, and reduce emissions (i.e, mitigation) (FAO, 2013). The findings demonstrate that increased education leads to greater public awareness of climate change and its risks and promotes public support and approval of climate action and environmental protection. Second, this essay provides new evidence that human capital accumulation, through higher education attainment, increases the adoption of sustainable farming practices, crop rotation, mixed cropping, improved seeds, irrigation, and soil conservation. Beyond on-farm adaptation, this study provides further evidence that human capital accumulation is crucial to building resilience against climate change through its positive impacts on crop loss management, job diversification, and enhanced household self–sufficiency.

These three studies are interconnected through their focus on different, yet complementary aspects of climate change adaptation in African agriculture. While the first essay examines household–level adaptation through labor markets, the second not only studies the impacts on resource use, but also explores how land institutions can address land market frictions to enhance resource allocation efficiency under climate stress. The third essay builds on this evidence to investigate how human capital development shapes climate beliefs, on-farm adaptation behaviors, and building resilience. Together, they provide a comprehensive picture of how different adaptation mechanisms interact and how enabling conditions can influence their effectiveness.

This dissertation makes several important contributions to the multiple strands of literature. First, it advances the literature on adaptation to climate change in developing countries by providing evidence on how rural households respond to climate shocks through various channels. The findings on labor reallocation and consumption smoothing contribute to our understanding of household risk management strategies (Dercon and Krishnan, 2000) and human capital and rural labor markets responses to weather shocks (Jayachandran, 2006; Branco and Féres, 2021; Colmer, 2021a,b). Second, it contributes to the literature on agricultural productivity and resource misallocation in developing countries (Restuccia et al., 2008; Restuccia and Santaeulalia-Llopis, 2017; Adamopoulos et al., 2022; Gollin and Udry, 2021) by showing how temperature shocks interact with institutional constraints to affect resource allocation efficiency. Third, it adds to the literature on the role of human in technology adoption in agriculture (Foster and Rosenzweig, 2010) and to the growing literature on the economic returns of free and compulsory schooling programs in SSA (Osili and Long, 2008; Oyelere, 2010; Chicoine, 2019; Ajayi and Ross, 2020) by demonstrating how education shapes climate change awareness and adaptation in agriculture.

The research also generates novel insights on policy complementarities in climate change adaptation. The findings suggest that the effectiveness of private adaptation strategies — whether through labor reallocation, resource adjustment, or technology adoption — depends crucially on enabling conditions like access to finance, secure property rights, and government investments in human capital development. This highlights the importance of coordinated policy interventions across multiple domains to build climate adaptation and resilience effectively.

The remainder of this dissertation proceeds as follows. Essay 1 examines household labor reallocation responses to drought shocks in Ethiopia. Essay 2 analyzes how rising temperatures affect resource misallocation in Tanzania's agriculture and explores the role of land property rights. Essay 3 studies how human capital development shapes climate change adaptation in Ethiopia. The dissertation concludes by synthesizing key findings and discussing their implications for climate adaptation.

Essay 1

Drought Shocks and Labor Reallocation in Rural Africa: Evidence from Ethiopia

Abstract

We study how rural households in Ethiopia adapt to droughts through labour reallocation. Using three waves of panel data and exploiting spatio-temporal variations in drought exposure, we find that households reduce on-farm work and increase off-farm self-employment in response to both short-term and persistent droughts, without abandoning family farming. Diversification into off-farm activities is driven by drought-related productivity declines in agriculture and contributes to consumption smoothing and food security. Households with better access to financial services are more likely to reallocate labour off-farm. Our results highlight the importance of strengthening the rural non-farm economy to enhance rural households' climate resilience.

Key Words: Drought shocks, climate change, labor markets, food security, Africa
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1.1 Introduction

Extreme weather events — such as droughts — have become more frequent with climate change and have negative impacts on farm production and income (Schlenker and Lobell, 2010; Lobell et al., 2011; Chavas et al., 2019; Ortiz-Bobea et al., 2021). Developing countries, particularly in sub-Saharan Africa (SSA), where agriculture is the mainstay of poor people's livelihoods, bear the brunt of these risks. The literature has looked at various ways in which rural households adapt to weather shocks, including asset sales, formal and informal insurance or adoption of climate-smart technologies. However, these adaptation strategies are often prohibitively costly, ineffective or unsustainable (Dercon and Krishnan, 2000; Giné and Yang, 2009; Karlan and Morduch, 2010; Dercon and Christiaensen, 2011). Much less is known about the extent to which households reallocate labor as a response to weather shocks, especially by shifting from farm to off-farm work, and how effective such reallocation is in protecting household welfare.

Weather shocks can prompt rural households to reallocate labor in different ways. Households may diversify their income sources. As off-farm jobs are typically less affected by weather disruptions, a certain shift from farm work to off-farm wage work is likely (Branco and Féres, 2021), to the extent that local labor markets have the capacity to absorb additional labor during times of weather shocks. If this is not the case, self-employment in non-agricultural businesses can be an alternative. Yet another alternative would be temporary or permanent migration to regions less affected by weather shocks or with better employment opportunities (Young, 2013; Rana and Qaim, 2024).

In this paper, we study labor reallocation decisions of rural households as a response to extreme weather shocks in the context of Ethiopia. We exploit spatio-temporal variation in exposure to droughts to look at the effects of short-term and persistent drought shocks on the probability of a household to be involved in farm work, off-farm wage employment and self-employment, as well as the labor time allocated to these employment categories. We also analyse to which extent the labor allocation decisions help smooth household consumption in the event of a drought shock. Ethiopia provides an interesting context for this study. First, in addition to economic vulnerability, Ethiopia exhibits a high degree of climate vulnerability, with a long history of droughts and an increasing frequency of extreme weather events (Viste et al., 2013; Mekonen et al., 2020). Second, Ethiopia is one of the most populous countries in Africa, and 80 percent of its rural population are employed in agriculture (UN-DESA, 2019). Third, agriculture in Ethiopia is predominantly smallholder farming with limited access to markets and advanced production technologies, resulting in widespread poverty.

Our results suggest that exposure to both short-term and persistent droughts has two main effects. First, it increases the likelihood of off-farm self-employment (OFSE) and reduces the likelihood of farm wage employment. Second, it increases the labor hours allocated to OFSE and reduces the labor hours allocated to on-farm wage and self-employment. Our results are consistent with droughts causing lower agricultural productivity and frictions in the labor market, leading to lower economic prospects in farm wage and self-employment and limited non-agricultural wage employment opportunities. We confirm the robustness of the findings using various empirical specifications. Finally, we show that OFSE is consumption smoothing.

Our study is related to the evolving literature on climate change adaptation and economic responses to weather shocks in developing countries. For instance, Di Falco et al. (2011) use data from smallholder farms in Ethiopia to show that the adoption of climate-smart technologies can help to increase food crop productivity. However, many smallholders are unable to adopt suitable farming innovations due to limited access to credit and information. Other studies look at links between weather shocks and labor market outcomes. For instance, Jessoe et al. (2018) use data from Mexico to show that in hot years, employment levels in wage work and non-farm jobs are reduced. In India, Jayachandran (2006) shows that weather-induced productivity shocks negatively affect poor rural households by significantly driving down wages. Emerick (2018) estimates that increased agricultural productivity due to abnormally high rainfall leads to an increase not only in agriculture but also in other local sectors due to sectoral linkages. On the other hand, Branco and Féres (2021) use data from Brazil to show that rural farming households increase their labor supply to non-agricultural sectors during droughts.

Colmer (2021a) finds that temperature-driven reductions in the demand for agricultural labor are correlated with increases in non-agricultural employment in India. This implies that the capacity of non-agricultural sectors to absorb workers might play a significant role in mitigating the economic impacts of negative agricultural productivity shocks. A few studies also examine links between weather shocks, child labor and education. For instance, Colmer (2021b) finds that increased rainfall variability is associated with less child labor and more schooling in rural Ethiopia, a finding the author describes is consistent with diversification strategies. However, the effects on child labor depend on a variety of socioeconomic conditions (e.g. Alam et al., 2022; Nordman et al., 2022). Furthermore, the effects of weather shocks on agricultural labor, both child and adult labor, may also depend on the adoption of climate-smart farming technologies (Fontes, 2020).

We contribute to these evolving bodies of literature in two important ways. First, while most existing studies focus on the effects of weather shocks in one single period[1], we look at short-term droughts and persistent droughts spanning over several years. Second, beyond our focus on labor reallocation, we also analyse effects of this reallocation on household welfare. A few previous studies investigate effects of weather shocks on welfare and interpret statistically insignificant results as evidence of successful adaptation (See, Emerick, 2018; Gao and Mills, 2018; Aggarwal, 2021) , yet the adaptation mechanisms are not studied explicitly. In our study, we show that labor reallocation to OFSE protects households from the negative consequences of drought on consumption and food security.

The rest of this paper is organised as follows: The next section describes the conceptual framework, while Section 3 discusses the data used. We present the empirical strategy and results in Sections 4 and 5, respectively, while Section 6 concludes.

1.2 Conceptual Framework

To study household labor allocation decisions, we apply a household production function framework, in which the household is the unit of production, consumption and decision-making (Udry, 1996). The household maximises utility by allocating available labor across different activities, such as farming, off-farm work and leisure, subject to

[1]One recent exception is Das et al. (2023), who estimate the impacts of subsequent droughts on farm revenues in Ethiopia.

resource constraints and the available production technology. An increase in agricultural productivity implies higher returns to agricultural inputs, thus attracting more labor into this sector (Becker, 1962). In contrast, weather shocks —such as drought — reduce agricultural productivity and income, thus lowering returns to agricultural labor and leading to a shift of labor away from farm towards off-farm economic activities (Lewis, 1954; Colmer, 2021b).

When faced with a reduction of agricultural productivity, a farm household may allocate (some of) its labor to off-farm employment. This can include wage employment—both in agricultural and non-agricultural activities—and OFSE. The availability and returns to off-farm employment depend on market wages and prices, which are influenced by local market conditions. The farm household may allocate more labor to off-farm work if this is less risky and (or) the returns are expected to be higher than in own farming.

However, out of the three off-farm employment alternatives that exist in principle, not all appear equally plausible in situations of drought. First, wage employment in agriculture is expected to be negatively affected by drought in the same way as own-farm employment. This is because weather shocks tend to be spatially concentrated and affect all local farmers at the same time. Hence, local agricultural employment opportunities and wages are expected to decline during drought, especially if out-migration is constrained (Jayachandran, 2006).

Second, at least in the short run, non-agricultural wage and self-employment are expected to be less affected by weather shocks and may, hence, offer higher returns to labor than agricultural employment. However, given widespread market failures, non-agricultural wage employment opportunities are typically scarce in rural areas, meaning that expected labor adjustments are not always feasible. Instead, households may turn to non-farm self-employment in their own small businesses, which are not always very lucrative (Haggblade et al., 2010; Davis et al., 2017) . In the long run, it is also possible that non-agricultural employment is negatively affected by persistent weather shocks, as income losses in agriculture can also spill over to other local sectors.

It is also worth noting that household decisions to reallocate labor may change over time. For instance, households may gradually use on-farm adaptation measures, such as the adoption of climate-smart technologies, thus decreasing their need for extensive labor reallocation in response to weather shocks. Other households may gradually abandon their own farming, thus increasing their labor supply to non-agricultural activities over time. In summary, how farm households respond to short-term and persistent weather shocks through labor reallocation and what this means for household welfare are important empirical questions that we address in this study in the context of Ethiopia.

1.3 Data

We combine data from two main sources. First, we use household data from the Ethiopia Socioeconomic Survey (ESS), a part of the World Bank's Living Standards Measurement Study. Second, we use weather data on temperature and rainfall from the National Oceanic and Atmospheric Administration (NOAA). These data are explained in more detail below.

1.3.1 Household Data

We use data from the 2011, 2013 and 2015 waves of the ESS to construct a panel of rural households. As we use panel data regression models with fixed effects, we only include households that were surveyed at least twice, leading to 9,968 household observations[2]. These data are nationally representative for rural areas of Ethiopia.

The main outcome variables, i.e. farm and off-farm wage and self-employment, are constructed based on the information available in the employment module of the household survey. The employment module contains information on the employment status of all household members aged 15 years and older in the last 12 months before the survey. We aggregate this information and create two household-level measures of employment, namely a dummy variable that is equal to one if any member of the household participates in each employment category (i.e. extensive margin), and a continuous variable measuring the percentage share of the household's weekly hours in each employment category (i.e. intensive margin). We also calculate the share of household members aged 15 years and older engaged in each employment category.

In terms of income variables, we calculate total farm and off-farm wage and business income, using data on wages, earnings from self-employment and other income sources. Variables on food and non-food consumption over the last 12 months before the survey are derived from the household expenditures modules[3]. To construct farm-related variables — such as land productivity, labor productivity (agricultural output value per labor-day), hired labor, crop and livestock income — we combine information from the agriculture and livestock modules of the questionnaire. Finally, we construct a series of household control variables, including gender, education, and age of the household head, family size, total land size, tropical livestock units (TLUs), and a dummy variable indicating access to formal financial services, specifically insurance and credit.

Table 1.1 presents sample summary statistics. Most households (81 percent) are self-employed on their farms. Both on-farm (2 per cent) and off-farm (9 percent) wage employment are low. Yet, 23 percent of the households are engaged in OFSE, which is the most common income diversification strategy in rural Ethiopia, as also pointed out by Bachewe et al. (2020). The average annual household consumption expenditure is Birr 20,280, of which food consumption accounts for 81 percent. Such a high food expenditure share is a clear indication of the low average living standard of rural households in Ethiopia.

[2]This comprises 3373; 3323 and 3272 rural households surveyed in waves 1, 2 and 3, respectively. As such, we drop only 93 rural households that were surveyed only once. The small number of dropouts reduces possible concerns about attrition bias.

[3]All monetary values are expressed in real terms, adjusted for inflation.

Table 1.1. Summary Statistics

Variable Description	N	Mean	SD
Panel A: labor Variables			
Share of households employed in on-farm wage job	9,968	0.02	0.14
Share of households employed in off-farm wage job	9,968	0.10	0.29
Share of households self-employed on-farm	9,968	0.81	0.39
Share of households self-employed off-farm	9,968	0.23	0.42
Share of weekly hours in on-farm wage jobs	9,968	0.01	0.05
Share of weekly hours in off-farm wage jobs	9,968	0.05	0.19
Share of weekly hours in on-farm self-employment	9,968	0.71	0.41
Share of weekly hours in OFSE	9,968	0.11	0.26
Household weekly labor hours	9,968	63.77	62.32
Panel B: Household Welfare Variables			
Gross annual value of crop production	8,420	8,899.07	43,343.93
Gross annual crop income	8,420	1,962.89	5,153.24
Total annual income	9,968	11,552.18	19,484.20
Total annual consumption expenditure	9,968	20,279.62	19,621.74
Annual expenditure food consumption	9,968	16,362.81	16,745.20
Annual expenditure on non-food consumption	9,968	3,619.96	7,598.33
Family farm labor (person days)	9,968	198.95	193.83
Hired farm labor (person days)	9,968	13.95	52.38
Land size in hectares	9,968	1.46	6.43
Land productivity	8,420	24,237.03	353,773.11
labor productivity	8,420	36.79	53.82
TLUs	9,968	2.62	5.81
Panel C: Weather Variables			
Drought months in pre-survey year	9,968	1.03	1.40
Drought months in pre-survey growing season	9,968	0.72	1.09
Hot months in pre-survey year	9,968	0.47	0.78
Average monthly temperature (°C)	9,968	0.29	0.60
Average monthly rainfall (mm)	9,968	21.05	3.39
Panel D: Household Controls			
Head age in years	9,968	46.14	15.42
Share of households with female head	9,968	0.24	0.43
Share of heads with post-primary school education	9,968	0.32	0.47
Number of household members	9,968	5.58	2.54
Share of households using financial services	9,968	0.13	0.33

Notes: The sample size for gross value of crop production, gross crop income, land productivity, and labor productivity is lower than the actual sample size because not all households practiced crop production in all the 3 survey years. All income and consumption values are measured in Ethiopian Birr per year (deflated). Land productivity and labor productivity are measured for each survey year as crop value in Birr per hectare and farm value in Birr per household labor-day, respectively. The average exchange rate was $1 = Birr 21.24. Additional details are shown in Appendix Table A1 in the supplementary data.

1.3.2 Weather Data

We extract gridded daily rainfall and maximum and minimum temperature data from the NOAA Climate Prediction Center covering the period 1980–2022[4]. The gridded daily rainfall in millimeters (mm) and surface temperature in degrees Celsius (°C) datasets have a spatial resolution of 0.50-degree by 0.50-degree latitude-longitude grid nodes. We leverage the enumeration area — equivalent of a village or cluster — geolocations to match the weather data with the household data.

Our main explanatory variable is drought, which we define as a continuous variable, namely as the number of dry months within the last year or, alternatively, within the last growing season before the survey. Drawing on the existing literature (Burke and Emerick, 2016; Lee et al., 2019; Kakpo et al., 2022), we calculate this drought variable as follows.

First, for each month of the year before the survey, we generate rainfall z-scores:

$$zscore^{RF}_{cmt} = \frac{RF_{cmt} - \bar{RF}_{cm}}{RF^{SD}_{cm}} \tag{1.1}$$

where RF_{cmt} is the total rainfall in cluster c (same as EA) in month m of year t; $\bar{RF}_{cm}$ is each cluster's 30-year (1981-2010) historical rainfall mean for a given month while RF^{SD}_{cm} is each cluster's historical (1980-2010) standard deviation of rainfall for a given month. This z-score corresponds to the Standardised Precipitation Index (SPI) in McKee et al. (1993)[5]. A z-score less than or equal to 1 indicates a drought month. Second, we sum up the number of drought months for each year before a survey wave. We refer to this variable as 'short-term drought', i.e. drought recorded over the last year before the survey. Additionally, we construct cumulative measures of drought by summing up the number of drought months recorded over periods of 2 and 3 years before the survey. We refer to these as measures of 'persistent drought'.

Given that the effects of drought can vary by agricultural season (e.g. Kakpo et al., 2022), we also generate the drought variable for the crop-growing season as the aggregate of drought months within the February–September window. Our definition of the growing season draws on the classification established by the Ethiopia Meteorological Agency[6] whereby we combine both the short and the long rain seasons into one[7].

Finally, to account for the fact that the occurrence and effects of drought are likely reinforced by extreme temperatures, we also generate temperature shock indicators as auxiliary weather shock proxies, which we measure as the number of hot months

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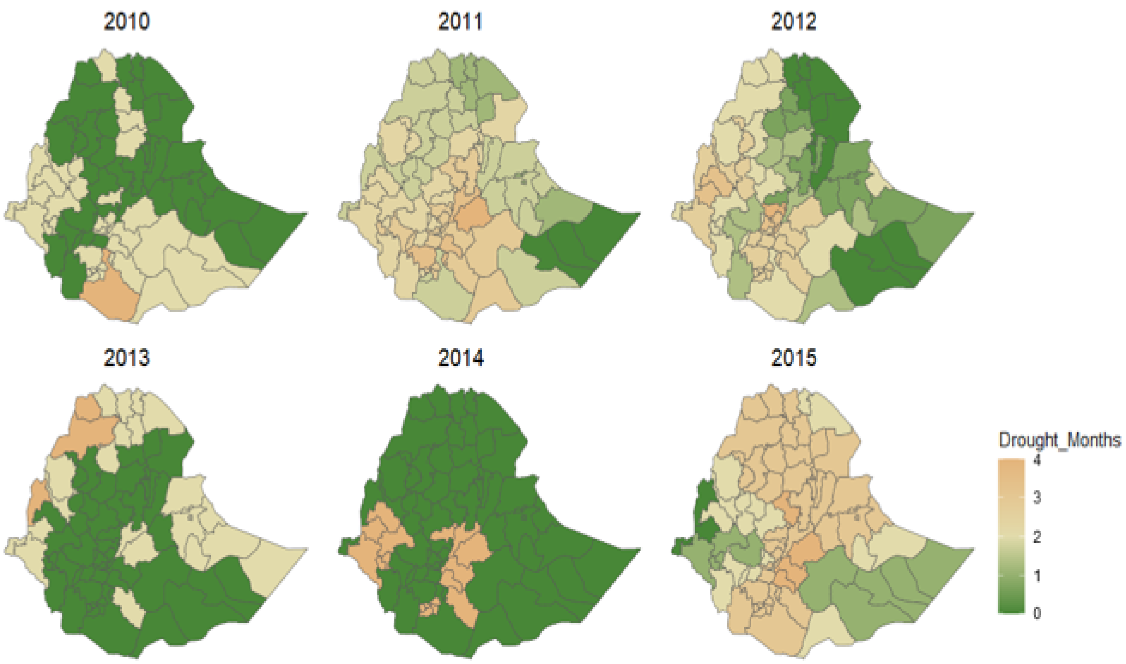
[4]The raw daily rainfall and temperature data can be extracted at:`https://psl.noaa.gov/data/gridded/data.cpc.globalprecip.html` and `https://psl.noaa.gov/data/gridded/data.cpc.globaltemp.html`

[5]An alternative drought index is the Standardised Precipitation Evapotranspiration Index (SPEI), which also includes temperature data in the calculations (Vicente-Serrano et al., 2010; Asfaw et al., 2018; Di Falco et al., 2020). We control for temperature in our regression models (see details further below).

[6]`http://www.ethiomet.gov.et/other_forecasts/seasonal_forecast`, accessed November 2022

[7]Ethiopia has three seasons, locally known as Bega (October to January), Belg (February to April) and Kiremt (May to September). During Bega, dry weather conditions prevail over much of the country. Belg is the short rain season for northeast, east, central and southern highland, and the main rain season for south and southeast. Kiremt is the main rain season across much of Ethiopia except for south and southeast. Crop growing varies across regions but falls within the two rain seasons. Since short rain and long rain seasons vary by region and given the limited short rain window, we construct one rain/crop growing season that combines both the short rain and the long rain seasons.

Figure 1.1. Spatio-temporal Variation in Drought Occurrence in Ethiopia



Source: Authors' compilation based on data from NOAA

over the last year, the last growing season, and the last dry season before the survey. Hot months are defined as the months with temperature z-scores greater than or equal to 2, indicating the occurrence of extreme temperatures.

Panel C of Table 1.1 presents the summary statistics of selected weather variables. On average, households experience 1 drought month in a year and approximately 0.7 and 0.3 drought months during the growing season and the dry season, respectively. Substantial variation in drought occurrence and intensity over time and space can be seen in Figure 1.1.

1.4 Empirical Strategy

1.4.1 Estimating Labor Reallocation Effects

We estimate the effects of drought shocks on household labor allocation decisions at the extensive and intensive margins using the following regression model:

$$L_{icdt} = \alpha + \beta D_{cdt-1} + \varphi W_{cdt-1} + \lambda X_{icdt} + \theta_d + \mu_t + \varepsilon_{ict} \tag{1.2}$$

where i, c, d and t subscripts index household, cluster, district (woreda) and time (year), respectively. L_{icdt} corresponds to household labor outcomes, i.e. farm and off-farm wage and self-employment dummies or, alternatively, the percentage share of weekly hours allocated to each employment category in the survey year. D_{ctd-1} is our main explanatory variable and corresponds to the number of drought months in the cluster in which household i is located, measured over the last year or the last growing season prior to the survey (*t-1*).

We include a vector of time-variant auxiliary weather variables at the cluster level, W_{cdt} (temperature shocks, monthly average temperature, monthly average rainfall), to differentiate drought shocks from other weather variations. We also control for a vector of household socioeconomic characteristics, X_{cdt}. We account for time-invariant unobserved heterogeneity at the district level by including district fixed effects, θ_D. Additionally, we include year fixed effects, μ_t, to account for country-wide shocks that would affect labor market conditions. We cluster standard errors at the cluster level.

We exploit spatio-temporal variation in individual households' exposure to drought shocks for identification. Our identification strategy relies on the assumption that droughts are exogenous, and—conditional on the controls and district and year fixed effects—there are no time-varying differences to drive household labor allocation decisions other than changes in weather conditions. In Appendix Table A1.1, we present a balance test showing that exposure to drought is not correlated with observable household characteristics and is thus plausibly exogenous. As such, our coefficient β in Equation 1.2 can be interpreted as the effect of an additional month of drought during the year (or during the growing season) on household labor allocation. We are also interested in possible heterogeneous effects by differentiating between households of different family size, market proximity, and those with differences in land ownership and access to formal financial services. Details of the analysis of heterogeneous effects are provided in Appendix 3.

As noted by Branco and Féres (2021), a crucial aspect of how drought shocks influence household decisions is the precise timing of the impacts. Plausibly, the effect of last year's drought on household labor supply in the current year may also depend on the past distribution of droughts. Similarly, exposure to drought in the current period may have varying effects on future household labor allocation decisions. Given this context, we estimate three additional sets of regressions to examine how the effects of droughts on household labor supply evolve over time. First, we estimate regressions using our measure of persistent drought (number of drought months observed over the last 2 and 3 years combined). Second, we use separate drought months variables for periods *t-1*, *t-2* and *t-3*. Third, we estimate the effects of drought shocks in 2010 on outcomes in 2011, 2013 and 2015.

We also carry out several robustness checks. First, we use household fixed effects instead of district fixed effects to focus on within-household changes over time. Second, given that weather shocks are possibly spatially correlated, we re-estimate our models using Conley robust standard errors (Conley, 1999; Hsiang, 2010)[8]. We follow Hirvonen (2016) and report Conley robust standard errors at various distance cutoffs. Third, we test whether the results are robust to alternative definitions of the outcome variables. Fourth, we test whether using an alternative weather database has a major influence on the results. Further details of these robustness checks are discussed below in the results section.

1.4.2 Mechanisms

In addition to estimating the effects of drought shocks on labor allocation, we also explore the main underlying mechanisms. Drawing on the literature (Zhang et al., 2018; Emerick, 2018; Colmer, 2021a; Olper et al., 2021; Ibanez et al., 2022), we look at

[8]Given the high dimensional fixed effects in our context, we implement this procedure using the reg2hdfespatial Stata package developed by Thiemo Fetzer: `http://www.trfetzer.com/conley-spatial-hac-errors-with-fixed-effects/`

agricultural production effects and local labor market dynamics. In terms of agricultural production, we hypothesize that household labor reallocation decisions can be explained by a direct negative effect of drought shocks on agricultural productivity. If land and agricultural labor productivity significantly decline as a result of drought, households may decide to reallocate (some of) their labor away from own farming to employment activities that are less affected by drought in order to protect their incomes and consumption. To test this mechanism, we estimate:

$$Y_{icdt} = \alpha + \sigma D_{cdt} + \varphi W_{cdt} + \lambda X_{icdt} + \theta_d + \mu_t \varepsilon_{ict} \tag{1.3}$$

where Y_{icdt} is the outcome variable for household *i*, such as agricultural land and labor productivity in year *t*. We follow the same identification strategy as in Equation 1.2. Notice that here we measure drought in the same period in which we observe the agricultural outcomes because the effects of weather shocks on agricultural production are contemporaneous.

In terms of labor market dynamics, we test if household labor allocation can be explained by frictions in local labor markets caused by droughts, both inside and outside of agriculture. First, we hypothesise that drought shocks shrink demand for hired on-farm labor due to negative effects on agricultural productivity. If this is the case, the supply of on-farm wage jobs would significantly diminish in the presence of droughts. We test this hypothesis by estimating the direct effects of droughts on households' demand for hired on-farm labor and corresponding daily wages paid. We expect that in response to drought, households will hire less labor, offer lower wages, or both. Second, we test whether labor demand and wages in non-agricultural activities are affected by droughts. It is difficult to predict *a priori* whether and to which extent non-agricultural labor demand responds to drought, as the effect will depend on the intensity of linkages between non-agricultural activities and agriculture and on local demand effects. The challenge is that we do not observe data on non-agricultural firms to directly measure their labor demand and wages over time. We therefore use non-agricultural wage income as a proxy for wages paid by firms.

1.4.3 Labor Allocation and Consumption Smoothing

We estimate the following regression model to assess the effect of labor allocation on household welfare following drought:

$$C_{icdt} = \alpha_1 D_{cdt-1} + \alpha_2 E_{idct} + \alpha_3 (D_{cdt-1} \times E_{icdt}) + \varphi W_{cdt-1} + \lambda X_{icdt} + \theta_d + \mu_t + \varepsilon_{ict} \tag{1.4}$$

where C_{icdt} is the measure of household welfare in year t. We define the outcome variable in different ways. First, we compute the value of household food and non-food consumption per adult equivalent. Second, following Swindale and Bilinsky (2006) and Kennedy et al. (2011), we use information on household weekly consumption of 12 different food groups to calculate the household dietary diversity score (HDDS) — a common indicator of food security. Third, given that HDDS in the 50th (median) and 75th percentiles of our sample are 5 and 7 food groups, respectively, we generate two separate dummy variables taking a value of one if the household HDDS is equal to or greater than 5 and 7, respectively. We interpret these two dummy variables as indicators of households being food-secure with medium and high levels of probability Kennedy et al. (2011). D_{cdt-1} is the number of drought months in the previous year, and E_{icdt} is the household number of weekly hours in off-farm employment in year *t*.

The interaction term between D and E informs us about the extent to which off-farm employment protects household consumption against the effects of drought. We control for the same household time-variant factors and district and year fixed effects as in the other models.

1.5 Results

1.5.1 Labor Reallocation: Extensive Margin

In this section, we discuss results from our regression models as specified in Equation 1.2.

Table 1.2. Effects of Drought on Household Likelihood of Employment in Different Job Categories

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage Employment				
Drought (year)	-0.004		0.002	
	(0.003)		(0.005)	
Drought during growing season		-0.009**		-0.006
		(0.004)		(0.008)
Mean of dep. variable	0.021	0.021	0.096	0.096
R-squared	0.499	0.499	0.628	0.628
Panel B: Self Employment				
Drought (year)	-0.013		0.051***	
	(0.008)		(0.010)	
Drought during growing season		-0.007		0.071***
		(0.012)		(0.016)
Mean of dep. variable	0.814	0.814	0.230	0.230
R-squared	0.807	0.807	0.229	0.229
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9968	9968	9968	9968

Notes: The dependent variable is a dummy that takes a value of 1 if a household has at least one member employed in each employment category and 0 otherwise. Drought refers to the pre-survey year and the pre-survey growing season. Household controls include age, gender and education of the household head, household size, land size and use of financial services. Cluster robust standard errors are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

For the dummy outcome variables, we employ a linear probability model due to its computational ease in absorbing many high-dimensional fixed effects (Guimaraes and Portugal, 2010). Panel A of Table 1.2 shows results for farm wage employment in columns (1) and (2), and for off-farm wage employment in columns (3) and (4). Panel B shows results for on-farm self-employment in columns (1) and (2), and for OFSE in columns (3) and (4).

The results in panel A of Table 1.2 show that exposure to drought in the previous year's growing season reduces households' probability of employment in farm wage jobs. Specifically, one extra drought month during the growing season decreases the household probability of having a farm wage job by 0.9 percentage points. We do not find any evidence of drought effects on the probability of off-farm wage employment, which may possibly be due to the scarcity of off-farm jobs in the context of rural Ethiopia.

In panel B of Table 1.2, we do not find statistically significant effects of drought on on-farm self-employment. However, we find evidence that an extra month of drought in the previous year increases the probability of OFSE by about 5 percentage points. The effect is amplified to 7 percentage points when the extra drought month occurs in the growing season. These findings highlight the important role of OFSE in mitigating agricultural income losses due to drought.

1.5.2 Labor Reallocation: Intensive Margin

Table 1.3 presents results from different specifications of Equation 1.2, where the dependent variable is the share of household weekly hours in each of the four job categories expressed in per cent. We find that one extra month of drought during the last growing season (column 2 of panel A) leads to a 0.35 percentage point decrease in the household labor share spent in farm wage employment. While this coefficient may appear small, it should be noted that the average household in the sample only spends 0.7 percent of its labor time on farm wage labor, meaning that the drought effect is equivalent to a reduction of 50 percent. For off-farm wage jobs, we find no significant effects of drought. Again, this may possibly be due to inadequate off-farm wage employment opportunities in the local contexts to absorb the surplus labor following drought episodes.

In panel B of Table 1.3, we find strong evidence that an increase in drought months significantly affects household labor allocation to both on-farm and off-farm self-employed activities. First, the results in columns (1) and (2) show that an additional drought month — during the year and growing season alike — leads to a 3–4 percentage point decrease in the household labor share spent in on-farm self-employment. Second, the results in columns (3) and (4) reveal that households respond to drought by allocating more labor to OFSE. We find that an additional drought month during the growing season leads to a 4.5 percentage point increase in the household labor share spent in OFSE (equivalent to a 40 percent increase evaluated at the sample mean of the dependent variable). Taken together, the results in Table 1.3 suggest that rural households in Ethiopia respond to frequent drought shocks by reallocating labor away from farming to OFSE. In fact, for drought months in the growing season, the combined decrease in the share of weekly labor hours in on-farm self-employment (4.064 percentage points) and farm wage employment (0.345 percentage points) is very similar to the increase in the share of labor hours in OFSE (+4.492 percentage points).

Table 1.3. Effects of Drought on Household Intensive Labor Allocation Margins

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage Employment				
Drought(year)	-0.151		0.412	
	(0.093)		(0.322)	
Drought during growing season		-0.345**		-0.074
		(0.161)		(0.482)
Mean of dep. variable (%)	0.730	0.730	5.297	5.297
R-squared	0.148	0.149	0.176	0.176
Panel B: Self Employment				
Drought(year)	-3.294***		2.812***	
	(0.834)		(0.610)	
Drought during growing season		-4.064**		4.492***
		(1.252)		(1.016)
Mean of dep. variable (%)	70.563	70.563	11.461	11.461
R-squared	0.263	0.262	0.194	0.195
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9968	9968	9968	9968

Notes: The dependent variable in all models is the share of household labor hours spent in a particular employment category expressed in percent of all labor hours (0–100 percent). Drought refers to the pre-survey year and the pre-survey growing season. Household controls include age, gender and education of the household head, household size, land size and use of financial services. Weather controls include temperature shock, average monthly temperature and average monthly rainfall. Cluster robust standard errors are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Additional results on the short-term and long-term effects of droughts are summarized in Appendix Table A1.2–Table A1.5. The effects of persistent droughts (drought months over last 2 and 3 years) reveal two important insights (Table A1.2 and Table A1.3). First, they point in the same direction as the effects of short-term drought, namely a labor reallocation away from farming to OFSE. Second, the effects of persistent droughts are somewhat smaller in absolute terms than the effects of short-term drought, suggesting that in the long-run households are possibly substituting on-farm adaptation for off-farm adaptation to some extent. The results in the Appendix Table A1.4 and Table A1.5 with drought months in specific past years provide additional insights, namely that the effects on labor reallocation tend to decrease over time.

The analyses of heterogeneous effects are shown in Table A1.6 and Table A1.9 in the Appendices. The results suggest that the labor reallocation effects from farm work to OFSE in response to drought are particularly strong among households with better access to formal financial services (Table A1.9). This is plausible, as access to financial services allows households to make investments that may be needed for running own non-farm business activities. This result is also consistent with previous research in Africa showing that access to credit can enhance the capacity of households to adapt to rainfall shocks (Tabetando et al., 2023).

1.5.3 Mechanisms

We now analyze some of the main mechanisms underlying the effects of drought on labor reallocation, as explained in Equation 1.3. The effects of drought on agricultural production are summarized in Table 1.4. The dependent variables are logarithm transformations, so the effects can be interpreted in percentage terms. As expected, drought negatively affects agricultural land productivity. One extra drought month in the year and growing season reduces land productivity by 27 percent and 33 percent, respectively. We also find negative effects on agricultural labor productivity. One extra drought month in the growing season reduces labor productivity by 17 percent.

Table 1.4. Effects of Drought on Agricultural Land and Labor Productivity

	Land productivity		Labor productivity	
	(1)	(2)	(3)	(4)
Drought (year)	-0.266***		-0.093***	
	(0.063)		(0.035)	
Drought during growing season		-0.328***		-0.167***
		(0.096)		(0.047)
Mean of dep. variable	24,237.03	24,237.03	39.56	39.56
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	8420	8420	8420	8420
R-Squared	0.596	0.597	0.629	0.631

Notes: Drought is measured in the survey year. The dependent variables are logarithms of land productivity and labor productivity for crop-producing households respectively. Household controls include age, gender and education of the household head, household size, land with size and use of financial services. Weather controls include temperature shock, average monthly temperature and average monthly rainfall. Cluster robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

The effects of drought on labor demand and wages are summarized in Table 1.5. We find negative but statistically insignificant effects of drought on the use of family labor on household farms. However, households significantly reduce the demand for hired labor on their farms. One additional drought month during the growing season reduces the quantity of hired labor by about 10 percent (panel A, column 4) and the wages paid to hired farm labor by about 13 percent (panel B, column 2). These results, taken together with the negative effects of drought on agricultural productivity, also explain why households reduce their labor supply to farm wage employment, as shown above. We find no evidence of significant effects of drought on non-agricultural wage income (Table 1.5, panel B, columns 3 and 4). Given that the labor supply of households to off-farm wage employment does not change significantly in response to drought (see Table 1.3), any changes in wage income would primarily be driven by changes in wage rates. The insignificant estimates in columns (3) and (4) of panel B suggest that non-agricultural wage rates do not respond much to short-term drought.

Table 1.5. Effects of Drought on Household Farm Labor Demand and Wages

	Family labor		Hired labor	
	(1)	(2)	(3)	(4)
Panel A: Farm Labor				
Drought (year)	-0.044		-0.022	
	(0.033)		(0.036)	
Drought during growing season		-0.030		-0.101***
		(0.037)		(0.038)
Mean of dep. variable	202.80	202.80	33.47	33.47
Panel B: Wages	Wages paid: hired labor		Non-agric wage income	
	(1)	(2)	(3)	(4)
Drought (year)	-0.054**		0.058	
	(0.038)		(0.083)	
Drought during growing season		-0.125***		0.031
		(0.038)		(0.083)
Mean of dep. variable	17.40	17.40	3437.49	3437.49
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9968	9968	9968	9968

Notes: Drought is measured in the pre-survey year. The dependent variables in panel A are logarithms of family and hired labor days and in panel B logarithms of wages paid for hired labor and non-agricultural wage income. Household controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls include temperature shock, average monthly temperature and average monthly rainfall. Cluster robust standard errors are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

1.5.4 OFSE and Consumption Smoothing

We now Equation 1.4 in order to analyze to what extent labor allocation to off-farm employment can contribute to consumption smoothing and food security. We focus on OFSE, as the results above indicate this is the main employment category that households reallocate labor to as a response to drought. We further focus our analysis on droughts occurring during the growing season, as this is the main period in which drought impacts are amplified.

The effects of drought on food and non-food consumption are summarized in Table 1.6. The results provide three insights. First, the drought coefficients in all models reveal that one additional drought month during the growing season leads to a 4–5 percent reduction in household food and non-food expenditures. Second, the coefficients for OFSE are all positive and statistically significant, implying that household labor allocation to OFSE is associated with higher food and non-food consumption. Third, the coefficients of the interaction term between drought and OFSE are positive and statistically significant, at least for food consumption (column 2), suggesting that OFSE contributes to consumption smoothing during and after drought episodes.

Table 1.6. Effects of Drought on Household Consumption

	Food consumption		Non-food consumption	
	(1)	(2)	(3)	(4)
Drought	-0.043***	-0.047***	-0.047***	-0.049***
	(0.012)	(0.012)	(0.016)	(0.017)
OSFE (log)	0.017***	0.011*	0.039***	0.037***
	(0.005)	(0.005)	(0.006)	(0.007)
Drought × OSFE (log)		0.009**		0.004
		(0.004)		(0.005)
Mean of dep. variable	3235.26	3235.26	733.70	733.70
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9968	9968	9968	9968
R-Squared	0.379	0.379	0.367	0.367

Notes: Drought is measured during the growing season. Dependent variables are logarithms of annual food and non-food consumption expenditures per adult equivalent. off-farm self-employment (OFSE) measured in hours. Household controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls are temperature shock, average monthly temperature and average monthly rainfall. Cluster robust standard errors are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Next, we analyze the effects of drought and OFSE on food security proxied by HDDS Table 1.7. We calculate HDDS z-scores to obtain a continuous outcome variable, in addition to two dummy variables for HDDSHDDS $\geq$ 5 and HDDS $\geq$ 7. The results in all models confirm that drought is associated with a decrease in food security. In particular, 1 additional drought month during the growing season reduces HDDS by about 0.05–0.06 standard deviations (Table 1.7, columns 1 and 2) and also lowers the likelihood of households being categorized as food-secure (columns 3–6). Further, OFSE is associated with higher levels of food security. The coefficients of the interaction term between drought and OFSE are all positive. In column (6), the interaction term is also statistically significant, suggesting that OFSE helps to reduce the likelihood of becoming food-insecure during or after drought episodes.

Table 1.7. Effects of Drought on Household Food Security

	HDDS (z-score)		HDDS ≥5 (dummy)		HDDS ≥7 (dummy)	
	(1)	(2)	(3)	(4)	(5)	(6)
Drought	-0.054***	-0.058***	-0.021**	-0.024**	-0.026***	-0.029***
	(0.017)	(0.017)	(0.009)	(0.009)	(0.008)	(0.008)
OFSE (log)	0.049***	0.044***	0.018***	0.015***	0.015***	0.011***
	(0.006)	(0.007)	(0.003)	(0.004)	(0.003)	(0.004)
Drought × OFSE (log)		0.008		0.005		0.006*
		(0.006)		(0.003)		(0.003)
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,968	9,968	9,968	9,968	9,968	9,968
R-Squared	0.387	0.387	0.282	0.282	0.252	0.252

Notes: Drought is measured during the growing season. OFSE measured in hours. Household controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls are temperature shock, average monthly temperature and rainfall. Cluster robust standard errors are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

1.5.5 Robustness Checks

In this section, we highlight results from additional estimations to show that our main results are robust to alternative model specifications. Results of these robustness checks are shown in the Appendix Table A1.10 – Table A1.19. First, we show that the same conclusions regarding reallocation of farm labor to OFSE following drought are supported when estimating the regression models with household fixed effects (Table A1.10 and Table A1.11). Also, the estimates of the effects of drought on household consumption and food security, and the role of OFSE for consumption smoothing during and after drought episodes, remain very similar when controlling for household fixed effects (Table A1.12 and Table A1.13).

Second, using various distance cutoffs, we re-estimate the models using Conley (1999) robust standard errors that account for spatial correlation (Appendix Table A1.14–Table A1.16). Third, we show that our results are robust to using the share of household members across the four job categories as an alternative dependent variable (Appendix Table A1.17). Finally, we confirm that the main findings are insensitive to the use of an alternative historical weather database[9] in Table A1.18 and Table A1.19.

[9] We use the University of Idaho's Terra Climate dataset: `https://data.nkn.uidaho.edu/dataset/monthly-climate-and-climatic-water-balance-global-terrestrial-surfaces-1958-2015`

1.6 Conclusion

We have analysed how rural households in sub-Saharan Africa adapt to drought shocks through labor reallocation, using representative household panel data from Ethiopia. We find that households reduce their labor time in farming as a response to drought, even though they do not abandon farming altogether. At the same time, households increase their labor time in off-farm activities. This partial switch from farming to off-farm activities is plausible because droughts significantly reduce agricultural productivity. We also show that droughts have negative effects on household food security, whereas the reallocation of labor time from farm to off-farm activities helps to smooth consumption and dietary diversity. In terms of off-farm activities, households increase their labor time in self-employed business activities as a response to drought, but not their labor time in off-farm wage employment. Our interpretation is that non-agricultural wage jobs are not sufficiently available in the local rural contexts of Ethiopia to absorb the additional labor supply during and after drought episodes.

Analysis of heterogeneous effects reveals that labor reallocation to OFSE as a response to drought is particularly strong for households with access to rural financial services. In other words, households with better access to rural finance find it easier to adjust their livelihoods to weather shocks. These households are better able to overcome liquidity constraints and other typical barriers for starting or expanding non-agricultural businesses.

Differentiating between short-term droughts and persistent droughts, we find similar labor reallocation effects in general. However, interestingly, the labor adjustments are somewhat stronger for short-term droughts. These differences suggest that households may possibly improve their adaptive capacity in the longer run by implementing on-farm adaptation strategies that complement labor reallocation to off-farm activities. Even though not analysed here in more detail, on-farm adaptation strategies may include the adoption of climate-smart technological innovations, such as irrigation, more tolerant seeds, and improved agronomic practices, among others.

Our findings highlight three important takeaways for policymaking. First, labor reallocation to off-farm activities is an important strategy for farm households in Africa to cope with weather shocks. As weather extremes tend to occur more frequently with climate change, policymakers should work towards increasing the size and improving the functioning of the rural non-farm economy. The creation of non-farm wage jobs, which are currently not sufficiently available, should have high priority. This does not mean a focus only on public-sector jobs. Policies to incentivise private firms to invest more in rural regions will also be important. Second, our findings of negative effects of droughts on food security and dietary diversity point to the need to develop tailored social protection schemes that particularly target the most vulnerable and those who lack the capacity to reallocate labor to off-farm activities. Third, our finding that access to formal financial services increases household OFSE as an adaptation strategy to drought calls for financial inclusion policies in rural settings. Such policies could help households to overcome liquidity constraints that undermine their ability to not only venture into alternative non-farm jobs but also to invest in climate-smart agricultural technologies.

Our study adds to the growing climate impacts and adaptation literature and supports the idea that weather shocks are partly contributing to the unique structural transformation patterns in Africa, which are characterised by high employment on small family farms combined with a strong diversification into off-farm activities, especially self-employed activities in small non-farm businesses (Davis et al., 2017; Sen, 2019; Christiaensen and Maertens, 2022). Future research should explore how non-agricultural rural employment can be fostered, how different types of jobs influence people's welfare and adaptive capacity and how non-agricultural employment is linked to agricultural development. Another important research direction is how smallholder farming can be made more climate-resilient through technological and institutional innovations.

Essay 2

Temperature, Land Property Rights, and Misallocation in Africa's Agriculture: Evidence from Tanzania

Abstract

There is new evidence that crop productivity in sub-Saharan Africa (SSA) has been declining over the past decade. One compelling explanation for the persistent trend in the current literature is the high levels of input misallocation. However, the influence of weather shocks on this misallocation remains underexplored, despite the fact that SSA faces threats from climate change more than the rest of the world. In this study, I combine satellite weather information with three waves of detailed plot-level crop production data from Tanzania to assess how severe temperature fluctuations affect allocative inefficiency. Using fixed effects panel regressions that exploit exogenous variation in daily average temperature during the growing season, I provide new evidence that increased exposure to daily temperatures above 30°C significantly contributes to higher aggregate misallocation, primarily driven by distortions in land and capital use. Furthermore, I find suggestive evidence that secure private property rights to land can alleviate this misallocation.

Key Words: Climate Change, Temperature, Misallocation, Agriculture, Africa
JEL Classification: Q12, Q15, Q54

This paper was accepted for oral presentation at the 2024 African Economic Conference (AEC), jointly organized by the African Development Bank (AfDB), the Economic Commission for Africa (ECA), and the United Nations Development Programme (UNDP), held in Gaborone, Botswana, from 23-25 November 2024, and at the Center for the Study of African Economies (CSAE) Conference 2025 at the University of Oxford in March 23-25, 2025.

2.1 Introduction

The most recent evidence reveals that in the last decade, crop productivity in smallholder farming systems in SSA has been declining by 3.5% per year (Wollburg et al., 2024). One plausible explanation for the persistent trend is the misallocation of production factors — i.e., land, labor, and capital — which is partly reinforced by insecure property rights to land (Restuccia et al., 2008; Gollin and Udry, 2021; Chen et al., 2023; Suri et al., 2024). At the same time, SSA faces greater threats from climate change (Deressa and Hassan, 2009) and increases in temperature in the region are projected to be higher than increases in the global mean (IPCC, 2019). While the evidence indicates that SSA agriculture suffers from resource misallocation and insecure land rights, which hinder aggregate productivity, there is still a limited understanding of how rising temperatures exacerbate this allocative inefficiency.

The impact of rising temperatures on agricultural productivity can be conceptualized through two primary channels. The first — widely covered in the current literature[1] — is a direct effect on crop health, where higher temperatures can alter growing conditions, potentially stressing plants and increasing vulnerability to pests and diseases. The second, less obvious, channel involves indirect effects through input distortions. As farmers respond to unfavorable climatic conditions, they may adjust their use of production inputs in ways that are not always optimal, leading to misallocation of resources. This indirect effect can exacerbate the challenges posed by temperature increases, potentially resulting in further declines in agricultural productivity beyond what would be expected from the direct impacts on crop health alone. Understanding both these direct and indirect channels is crucial for developing effective strategies to mitigate the negative impacts of rising temperatures on agricultural systems, particularly in SSA.

In this paper, I use detailed plot-level data merged with satellite weather information from Tanzania to provide new evidence on the contemporaneous effects of temperature on resource misallocation and the role of secure land property rights in alleviating such inefficiencies. To achieve this, I first exploit the panel structure of the data to estimate household permanent total factor productivity (TFP), which is a widely used proxy for household farming ability. Following Hsieh and Klenow (2009), I then use the permanent TFP estimates to recover three measures of misallocation: marginal product of land (MPLa), marginal product of capital (MPK), and total factor productivity of revenue (TFPR), which is a composite measure of aggregate misallocation. Tanzania provides a unique and relevant context to investigate for three important reasons. First, the latest estimates of the International Labor Organization (ILO) show that 65%[2] of the country's population is employed in agriculture. Second, land market frictions due to incomplete land market are salient in Tanzania (Manysheva, 2022). This is largely attributed to the country's current land tenure system, where most of the land is under customary rights following the ratification of the 1999 Village Land Act, which grants tenure security at the village level. Through this Act, village leaders have power over land transactions and disputes[3].

To estimate the contemporaneous effects of temperature on misallocation, I employ an empirical strategy that exploits exogenous variation in the share of days in

[1](See, Schlenker and Roberts, 2009; Tito et al., 2018; Chavas et al., 2019; Ortiz-Bobea et al., 2021; Wang et al., 2022)

[2]`https://ilostat.ilo.org/data/`

[3]`https://tanzanialaws.com/v/412-village-land-act`

the growing season whose average daily temperature falls in a certain temperature bin. I classify the average daily temperature into four bins: $\leq 20°C$, >20$\leq$ $25°C$, >25<30°C and $\geq$ $30°C$,. The main strength of this approach is that it accommodates any non-linear relationships between temperature and outcome variables (Deschênes and Greenstone, 2011; Zhang et al., 2018; Heutel et al., 2021; Ponticelli et al., 2023). I have two main results. First, a one percentage point increase in the number of days above 30°C during the growing season is associated with an increase in aggregate misallocation by approximately 2.2% and land and capital misallocation by approximately 2.5% and 2.1%, respectively. Relative to the mean growing season temperature days above 30°C, this implies that a 15% increase in the share of days during the growth season with an average daily temperature of at least 30°C leads to aggregate misallocation of approximately 33% driven by land and capital misallocation of approximately 38% and 32%, respectively. Second, I find suggestive evidence that for the same one percentage point increase in the growing season days with a daily temperature of at least 30°C, households with secure private property rights to land experience lower aggregate and land misallocation.

This paper relates to two strands of literature in development economics. First, a growing body of work has documented the extent of misallocation and the economic gains from addressing agricultural resource misallocation(Hsieh and Klenow, 2009; Restuccia and Santaeulalia-Llopis, 2017; Adamopoulos et al., 2022). Ranasinghe (2024) show that female establishments in both low- and middle-income countries face higher input misallocation and that eliminating these distortions significantly improves female market shares and total factor productivity (TFP), especially in poorer countries. The evidence linking resource misallocation to reduced agricultural productivity is particularly strong in SSA, where Chen et al. (2022) quantitatively demonstrate that solving land misallocation can substantially reduce agricultural income inequality and poverty in Malawi.

The paper also connects to the literature examining how policy reforms that guarantee secure land property rights can address resource misallocation through their potential to eliminate land market frictions. For instance, Zhang et al. (2023) find that an increase in farmland leasing reduces land misallocation and increases TFP in China. These findings are consistent with Gao et al. (2021) and Chen et al. (2023) which show that land certification reforms lead to land and labor reallocation to more productive farms in China and Ethiopia, respectively. This positive link between land property rights and resource allocation, comprehensively summarized in Galiani and Schargrodsky (2011), is further supported by evidence that land certification and contracting laws promote efficient land reallocation in various contexts (Gai et al., 2020; Chari et al., 2021; Manysheva, 2022).

I contribute to these strands of literature in two important ways. First, while existing studies have extensively documented the extent of resource misallocation in agriculture and its implications for productivity, this study is the first to directly show how temperature shocks interact with and amplify these allocative inefficiencies. Using detailed micro-data from, I demonstrate that severe temperatures exacerbate preexisting agricultural resource misallocation, revealing a previously unexplored channel through which climate change could affect agricultural productivity in developing countries.

Second, I extend the literature on land institutions by showing how property rights that guarantee private tenure security can potentially reduce temperature-driven misallocation. By defining land property rights beyond conventional legal documentation alone, this study acknowledges the dynamics of tenure security in most SSA countries, where land is predominantly under communal rights. This distinction proves crucial, as the results reveal that while private property rights can effectively mitigate temperature-induced misallocation, communal rights systems may not offer similar protection. These findings suggest an important new dimension to consider in land tenure reforms: their role in building climate resilience through improved resource allocation efficiency.

The rest of the paper proceeds as follows. The next section discusses methods: data sources, estimation of misallocation, and econometric strategy. Section 3 presents and discusses the results. Section 4 concludes.

2.2 Methods

2.2.1 Data

I combine the first three waves of Tanzania's Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS – ISA) with satellite weather data (temperature and rainfall) from CHIRTS and CHIRPS.

The LSMS-ISA provides detailed household and plot-level information on agricultural production in both the long-rain and short-rain seasons. As such, I can observe information on household sociodemographics, plot characteristics, plot decision maker, crop output, and production inputs. I focus on the growing seasons because common temporary food crops such as maize, cowpeas, beans, millet, sorghum, and groundnuts are grown during this period.

Farm output and inputs: Households report yield quantities for all crops produced in each season for each plot owned and crop-specific prices. Given that households practice inter-cropping and variations in units used to report crop yields, I measure plot output as the value of all temporary food crops produced on the plot during the main growing season for each survey wave. Where unit crop prices are not reported, I infer prices from the unit value by dividing the value of sales for that crop by the quantity sold. Where sales are not reported, I use the median unit value of the crop at the district level for which at least 10 observations of market prices are reported.

For farm inputs, first, I have information on the size of each plot in acres, which I convert into hectares. Second, I use the reported family and hired labor for each plot to compute total labor in person-days employed on each plot during the growing season. Third, households also report information on capital input for each season in terms of farm equipment owned and rented and their respective present values. I use this information to calculate the total value of capital input as the sum of the values of owned and rented farm equipment. However, it is important to note that I do not observe capital inputs by plot but only by household. As a result, household plots are effectively assigned the household's value of capital used in the growing season. This assumption is plausible because it is common practice for rural households, particularly in poor countries, to use the same farm equipment owned or hired on all the plots they operate. Lastly, households provide information on intermediary inputs such as fertilizers (both organic and inorganic) and pesticides used on each plot for each growing season. Given that these intermediary inputs are reported in different units, I value them using median national prices.

Household characteristics: The LSMS-ISA also collects detailed household and individual data on age, education, health, employment, and occupational choices, other sources of income, asset ownership, food and non-food consumption expenditures, access to agricultural extension services, use of formal financial services, as well as information on who in the household makes farming decisions on each operated plot. I use this information to construct a host of household observable characteristics and to identify the gender of the main decision maker for each operated plot. In addition, households report information on whether each operated plot has a legal document, whether the plot was obtained free of charge, and whether the household has the right to leave the plot fallow and to either sell or use it as collateral. I use this information to generate five measures of property rights to land.

Weather data: Given that the LSMS-ISA data are georeferenced at the village level (enumeration area), I extracted the high resolution (0.05° x 0.05°, approximately 5 kilometers) at the village level. The weather variable of interest is the temperature. Therefore, I use the daily maximum and minimum temperature data to first compute the daily average temperature for each survey year. I classify the average daily temperature into four bins: less than 20°C, between 20°C and 25°C, between 25°C and 30°C and above 30°C. For each temperature bin in a survey year, I calculate the number of days in the growing season and year for which the average daily temperature falls in each of the four bins. I define the growing season as the period that covers both the short-rain (October–December) and the long–rain season (March–May) in Tanzania.[4] I also generate daily average temperature for both the growing season and year.

Final sample: I leverage the village georeferences provided in the LSMS-ISA to merge weather information with household surveys. In my main analysis, I restrict the final sample to plots that were surveyed at least twice and cultivated during the growing season. Lastly, I restrict the sample to plots in mainland Tanzania[5]. This results in a total sample of 11,747 plots with 75.4%, 24.1% and less than 1% being men-managed, women-managed, and jointly managed during the growing season, respectively.

2.2.2 Estimating Household TFP

Following Hsieh and Klenow (2009), I assume an economy comprising heterogeneous households that operate farms (plots) i in each period t. Households differ in ability and in each growing season are endowed with at least one land parcel (plot) l_{it} and capital k_{it} to produce a homogeneous good according to the following Cobb-Douglas technology that exhibits decreasing returns to scale:

$$\bar{y}_{it} = (s_i \xi_{it})^{1-\gamma} \left[k_{it}^{\alpha} (q_{it} l_{it})^{1-\alpha} \right]^{\gamma}, \quad \alpha, \gamma \in (0,1) \tag{2.1}$$

Where $\bar{y}_{it}$ is the real value added for plot i during the growing season in period t computed as the value of real output y_{it} less total value of intermediary inputs such as fertilizers and pesticides; k_{it} is the capital input and l_{it} is the operated plot-size in hectares adjusted for land quality q_i. The parameter γ is the span of control governing

[4]There are two growing seasons in Tanzania: the long-rain season, locally known as masika, during the March-May months and the short-rain season (locally known as vuli) from October to December. `https://climateknowledgeportal.worldbank.org/country/tanzania/climate-data-historical`

[5]I focus on mainland Tanzania and exclude Zanzibar because the extracted weather data has missing weather information for several years for Zanzibar.

the plot-level returns to scale and α is a factor share parameter. Notice that the TFP has two components: the permanent term s_i — ability — and the transitory component ξ_{it} which consists of weather and idiosyncratic shocks. I abstract the production function from differences in labor because it is difficult to value the on-farm labor given it is mainly supplied by household members. However, I account for the potential variation in labor input by converting the real value added, capital, and land inputs into per capita labor-days.

In addition, I adjust the land input for the land quality as follows. Following Chen et al. (2022), I construct a land quality index q_i for each plot by regressing the plot output y_{it} on a set of observable plot characteristics: soil type, soil quality, slope, and erosion while controlling for plot, year and district fixed effects and standard errors clustered at the village level. I find a statistically significant positive correlation between this index and self-reported plot market value as shown in Table A2.3, which implies that it is plausibly a reliable measure of land quality.

To estimate Equation 3.1, I set α = 0.274 and γ = 0.54 to match the capital and land income shares of 0.147 and 0.389, respectively, for African agriculture as reported in Chen et al. (2022). Based on the α and γ values, I residually estimate TFP for each plot operated by the household in each year, which I collapse by household and year to get average household TFP. My interest, however, is to measure household resource allocations relative to their ability. However, recall that the TFP measure comprises the transitory component ξ_{it} and therefore does not provide a precise measure of household ability (i.e. permanent TFP, s_i). To recover the benchmark measure of permanent TFP, I use panel data methods that account for spatial and temporal variations in productivity (Bolhuis et al., 2021; Chen et al., 2022; Adamopoulos et al., 2022). More details on this approach are relegated to the appendix section 3 .

2.2.3 Measuring Misallocation and Efficient Allocations

The starting point for assessing misallocation is to compare household actual allocations — observed in the data — with their counterfactual efficient allocations relative to their ability. I obtain efficient allocations by solving the following social planner problem:

$$\underset{\{k_i,l_i\}}{\text{Max}} \quad Y^e_{rt} = \sum_{i=1}^{n_r} s_{irt}\left(k^{\alpha}_{irt} l^{1-\alpha}_{irt}\right)^{\gamma} \tag{2.2}$$

$$\text{Subject to} \quad K_{rt} = \sum_{i=1}^{n_r} k_{irt}, \quad L_{rt} = \sum_{i=1}^{n_r} l_{irt}$$

where K_{rt} and L_{rt} are the total capital and land endowments available in households' respective regions r during period t.

With ability s_i residually estimated from Equation 3.1, I first solve for each household's plot-level efficient allocations for capital k^e_{irt} and land l^e_{irt} in the growing season as their productivity shares of fixed regional capital K_{rt} and land L_{rt} endowments:

$$k^e_{irt} = \frac{s_{irt}}{\sum_{i=1}^{n_r} s_{irt}} K_{rt} \quad , \quad l^e_{irt} = \frac{s_{irt}}{\sum_{i=1}^{n_r} s_{ir}} L_{rt} \tag{2.3}$$

Drawing on Equation 3.1, it follows that household's efficient crop output for any operated plot in their respective regional economies with efficient allocations can be expressed as:

$$y_{ir}^{e} = \frac{s_{ir}}{\left[\sum_{i=1}^{n_r} s_{ir}\right]^{\gamma}} \left[K_{tr}^{\alpha} L_{tr}^{1-\alpha}\right]^{\gamma} \tag{2.4}$$

Next, I estimate different measures of resource misallocation that are common in the literature (Hsieh and Klenow, 2009; Hopenhayn, 2014; Adamopoulos et al., 2022; Chen et al., 2022). First, using the actual and derived efficient allocations, I compute the marginal products of land and capital for each operated plot. In an economy with efficient allocations, both the marginal product for land (MPLa) and the marginal product for capital (MPK) should equalize across farms. I formally compute the actual MPLa and MPK as:

$$\text{MPLa} = (1-\alpha)\gamma\frac{y_{it}}{l_{it}} \quad , \quad \text{MPK} = \alpha\gamma\frac{y_{it}}{l_{it}} \tag{2.5}$$

I follow the same approach in Equation 3.5 to derive the marginal products under efficient allocations by replacing the actual output, labor and capital with the respective efficient values estimated from Equation 3.3 and Equation 3.4.

Second, following Hsieh and Klenow (2009) I derive, total factor productivity of revenue (TFPR), a summary measure of input distortions which is simply the ratio of output to inputs:

$$\text{TFPR} = \frac{y_{it}}{k_{it}^{\alpha} l_{it}^{1-\alpha}} \quad , \quad \text{TFPR}_{it}^{e} = \frac{y_{it}^{e}}{k_{it}^{e\ \alpha} l_{it}^{e\ 1-\alpha}} \tag{2.6}$$

Where $TFPR_{it}$ and $TFPR_{it}^{e}$ are the actual and efficient TFPR, respectively. In efficient allocation, the TFPR should be equalized across production units. Thus, dispersion of TFPR would be indicative of misallocation.

2.2.4 Summary Statistics

The plot-level summary statistics presented in Table 2.1 reveal that the average size of the household plot is 1 Ha. Most plots are characterized by insecure land property rights. In particular, only 10% and less than 40% of the operated plots report having a title and any legal document, respectively. In addition, households report having the right to leave the plot fallow or the right to sell and use it as collateral on about 36% and 34% of the plots. The summary statistics at the household level in Table A2.1 further reveal that the average household head is about 50 years old, with the majority (76%) being men.

The summary statistics for temperature and rainfall are presented in Table 2.2. I classify temperature in bins and report the percentage share of days in the growing season and in the year for which the average daily temperature falls within that bin. Most days during the growing season fall in the $>25<30°$C temperature bin.

The descriptive evidence for the presence of distortions and misallocation is visually summarized in Figure 2.1. Panels (a) and (b) in Figure 2.1 show the relationship between permanent TFP of the household and the actual plot level (blue) and efficient (dashed red) of land and capital during the growing season. The actual inputs (land and capital) are evidently not positively correlated with permanent TFP, providing the first descriptive evidence of inefficient allocations. Additionally, panels (c) and (d) reveal that the actual MPLa and MPK are not equalized across farms — a pattern that is inconsistent with efficient allocations. Lastly, the evidence summarizing the distortions faced by a decision maker in both land and capital allocations measured by TFPR is presented in panel (e) of Figure 2.1. Contrary to theoretical predictions , the graph shows that the TFPR is not equalized across plots.

Table 2.1. Plot-level Summary Statistics

	N	Mean	SD
Panel A: Production			
Crop yield (kg)	11747	1,596.943	73,055.153
Crop value (TSh)	11747	203,264.340	580,166.262
Capital	11747	1,239,579.781	8,498,835.180
Plot size (ha)	11747	1.130	2.544
Labor (person-days)	11747	86.286	80.611
Value of inputs (Tsh)	11747	17,484.360	90,800.311
Panel B: Tenure Rights			
Titled	11747	0.099	0.298
Legal document	11747	0.377	0.485
Fallow rights	11747	0.359	0.480
Sale rights	11747	0.338	0.473
Acquired free of charge	11747	0.071	0.257

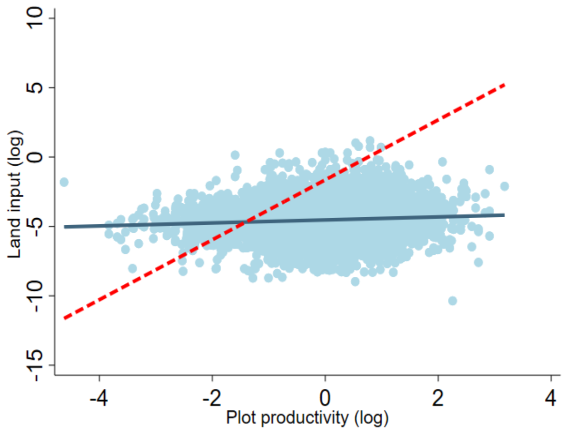
Table 2.2. Weather Summary Statistics

	N	Mean	SD	Min	Max
Weather during growing season					
Pct.days $\leq 20^{\circ}$C	1227	2.93	11.49	0.00	100.00
Pct.days $>$20$\leq 25^{\circ}$C	1227	30.31	33.76	0.00	100.00
Pct.days $>$25$<$30°C	1227	51.38	31.36	0.00	100.00
Pct.days $\geq 30^{\circ}$C	1227	15.37	24.76	0.00	100.00
Average temperature	1227	26.51	3.01	16.64	31.89
Precipitation (mm/day)	1227	3.77	1.29	1.18	11.15
Weather during the year					
Pct.days $\leq 20^{\circ}$	1227	5.96	15.22	0.00	100.00
Pct.days $>$20$\leq 25^{\circ}$C	1227	33.03	31.48	0.00	99.18
Pct.days $>$25$<$30°C	1227	49.08	29.52	0.00	99.73
Pct.days $\geq 30^{\circ}$C	1227	11.93	19.05	0.00	100.00
Average temperature	1227	25.86	3.06	16.11	31.36
Precipitation (mm/day)	1227	2.64	0.77	0.91	7.14

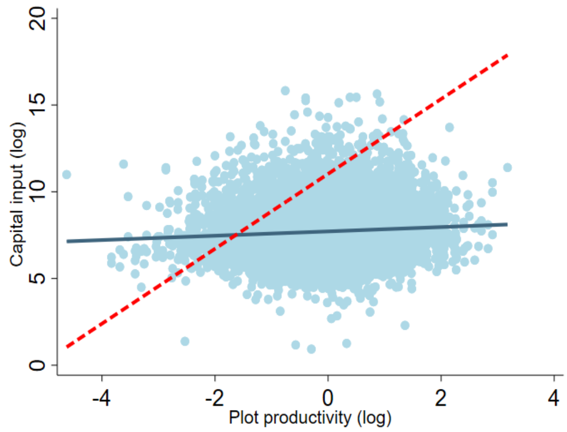
Notes: N is the number of villages observed in the three survey waves.

Figure 2.1. Input Use and Marginal Products: Actual and Efficient Allocations

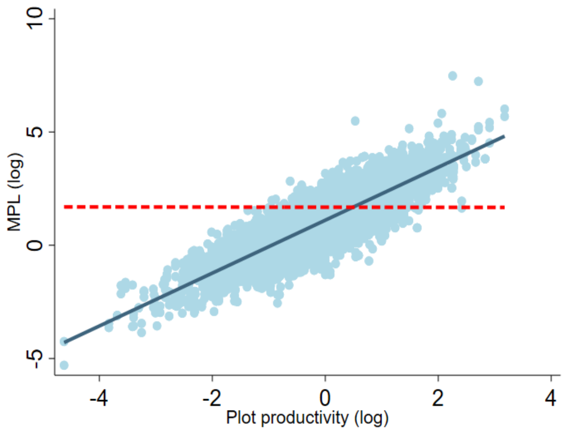
(a) Land Size vs. Plot Productivity



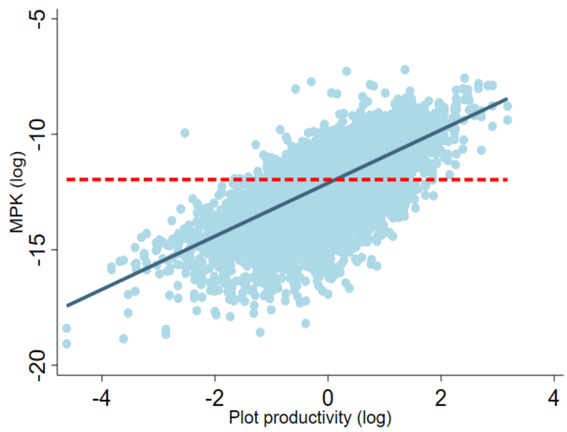
(b) Capital vs. Plot Productivity



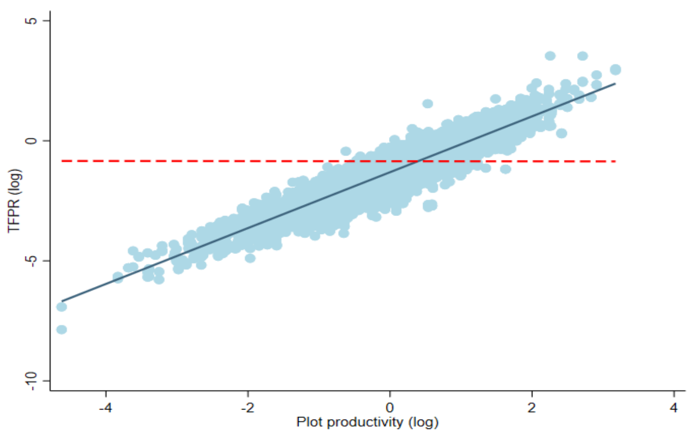
(c) MPL vs. Plot Productivity



(d) MPK vs. Plot Productivity



(e) TFPR: Actual vs. Efficient



Notes: Each blue dot represents a household plot in the data. The blue line represents actual allocations, whereas the red dashed line represents counterfactual efficient allocations. MPL: marginal product for land; MPK: marginal product for capital; TFPR: Total factor productivity of revenue.

2.2.5 Econometric Strategy

To analyze the contemporaneous effects of temperature on resource misallocation, I estimate the following fixed effects regression specification:

$$Y_{ihv(d)t} = \sum_{m} \beta^m T^m_{v(d)t} + \alpha P_{v(d)t} + \gamma X_{hv(d)t} + \delta_h + \theta_i + \mu_t + \epsilon_{ihv(d)t} \tag{2.7}$$

where *i* denotes plot, *h* indexes household, *v(d)* denotes village *v* in district *d* where the household and the plot are located and *t* represents the survey year (or wave). $Y_{ihv(d)t}$ are the three measures of misallocation — dispersion in TFPR, MPLa and MPK relative to district mean — which I calculate as the absolute deviations of (log) TFPR, MPLa and MPK from the region (district) mean. Note that I use the absolute values of the logarithmic measures of misallocation, since the deviations from district mean can be great or less than zero, both of which indicate misallocation. As such, I can interpret the positive temperature coefficients as a movement away from efficiency (more misallocation) without any ambiguity. T^m are the temperature bins that capture the percentage share of days in a given village and the growing season whose average daily temperature is within a certain bin *m*. Recall that I have four temperature bins: $\leq$ 20°C, >20$\leq$ 25°C, >25<30°C, and $\geq$ 30°C. This approach has become popular because it accommodates any non-linear relationships between temperature and outcome variables (Deschênes and Greenstone, 2011; Zhang et al., 2018; Heutel et al., 2021; Ponticelli et al., 2023). Given that the temperature bins are linearly independent and add up to 100, I omit the >25<30°C bin — which has the largest share of growing season days and because the daily average temperature of the growing season falls within this bin — to avoid multicollinearity. The coefficient estimates β^m that are identified through year-to-year exogenous fluctuations in average daily temperatures are interpreted as the effect of a one percent increase in the growing season days in a certain bin relative to a one percent growing season days increase in the omitted 20–25°C bin. However, my main coefficient of interest is $\beta^{>30}$ as it captures the effect of the growing season days with severe temperature (i.e., above 30°C).

I control for average daily precipitation $P_{v(d)t}$ and its square term because temperature shocks can amplify or diminish depending on the amount of precipitation. Second, I control for household characteristics $X_{hv(d)t}$ which comprise the gender, age, and years of schooling of the household head and the household size. I also include household fixed effects δ_h and plot fixed effects θ_i to control for the time-invariant household and plot heterogeneity, respectively and interview year fixed effects μ_t to control for annual shocks such as national policies. To account for the potential spatial correlation in the error term $\epsilon_{ihv(d)t}$, I cluster the standard errors at the village level. However, as a robustness, I re-estimate the specifications using heteroskedasticity and autocorrelation consistent (HAC) standard errors proposed by Conley (1999) with distance cut-offs of 50KM, 100KM and 200KM and time lags of 5 and 10 years.

In addition to estimating HAC standard errors, I also perform three additional robustness tests. First, I replicate the baseline model using the number of days in the year in which the daily average temperature falls in the three bins. It is plausible that household responses to temperature shocks are not limited to the growing season alone. Exposure to temperature shocks prior to the growing season may cause frictions in factor markets and influence decisions about the allocation of resources by households *exante*. As such, we expect annual temperature shocks to equally drive resource misallocation. Second, I replicate Equation 2.7 using an alternative outcome variable. In particular, I use counterfactual misallocation measures that I compute assuming efficient allocations. Here, we would expect higher temperatures to shift households away from efficient allocations. Lastly, I test the robustness of the baseline results by choosing a different temperature bin as an alternative way to account for multicollinearity. In particular, I omit the $<20°$C temperature bin and reestimate Equation 2.7 using the 20–25°C, 26–30°C, and $>30°$C temperature bins in all regression specifications. The estimated temperature coefficients are thus interpreted relative to the omitted $<20°$C bin.

Next, to examine the role of land property rights on the misallocation driven by high temperatures, I extend Equation 2.7 as follows:

$$Y_{ihv(d)t} = \sum\nolimits_m \beta^m T^m_{v(d)t} + \lambda(T^{30}_{v(d)t} \times R_{ihv(d)t}) + \alpha P_{v(d)t} + \gamma X_{hv(d)t} + \delta_h + \theta_i + \mu_t + \epsilon_{ihv(d)t} \quad (2.8)$$

I introduce an interaction term between the share of growing season days with high temperature (i.e., temperature $>30°$C) and an indicator of land right $R_{hv(d)t}$. Notice that $R_{hv(d)t}$ does not independently enter the equation because it is absorbed by the plot fixed effects,θ_i. I use five different definitions of land property rights that offer varying degrees of tenure security in line with the two property rights regimes in Tanzania: private and customary rights. I first measure land property rights at the household level as follows: (i) whether the plot was acquired free of charge; (ii) whether a plot has a title deed or any other legal document; (iii) whether the household has right to leave the operated plot fallow; and (iv) whether the household has right to sell the plot or use it as collateral. Second, given that the Tanzania's Village Land Act of 1999 grants customary rights at the village level, I generate a dummy variable that takes the value of 1 if each of the household operated plots is located in the village that has a certificate of village land.

Note that in Equation 2.8, the coefficient estimates β^m capture the effects of temperature on misallocation as in Equation 2.7, which is common for both households with and without secure property rights for the operated plot. On the other hand, the coefficient λ captures the differential effect of temperature for plots with the aforementioned land property rights. I interpret this coefficient as an additional influence of land property rights on temperature-driven misallocation.

2.3 Results

2.3.1 Temperature and Misallocation

I begin by reporting the results of estimating Equation 2.7 summarized in Table 2.3. The dependent variables in the coefficient columns are logarithmic values of the dispersion in TFPR, MPLa, and MPK computed as absolute deviations from the yearly district mean. Recall that an increase in the dispersion of TFPPR, MPLa and MPK is informative of implicit resource distortions, and thus misallocation.

The results show that higher temperatures are associated with an increased dispersion in TFPR and marginal products of land and capital. More specifically, compared to a one percentage point increase in the share of growing season days with 20-25°C, an extra percentage point increase in the share of growing season days above 30°C increases aggregate resource misallocation (TFPR) by 2.2% and land and capital misallocation by 2.5% and 2.1%, respectively. Given that the growing season experiences on average 15% days with a daily temperature of at least 30°C, these results imply that a 15% increase in the share of days of the growing season with temperature above 30°C increases aggregate misallocation by approximately 33% which can be explained by an increase in land and capital of approximately 38% and 32%, respectively.

Table 2.3. Temperature and Misallocation

	Log TFPR	Log MPLa	Log MPK
Pct.days $\leq 20°$C	-0.003	-0.002	-0.014
	(0.011)	(0.013)	(0.013)
Pct.days >20≤25°C	-0.007	-0.005	-0.020***
	(0.006)	(0.007)	(0.006)
Pct.days $\geq 30°$C	0.022***	0.025***	0.021**
	(0.006)	(0.009)	(0.009)
Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Plot FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	11615	11615	11615
R^2	0.908	0.877	0.842

Notes: The temperature bins of the share of growing season days are relative to the omitted >25<30°C bin. Controls include rainfall, age, gender, and education of the head of household and household size. Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

The magnitude of these effects is particularly worrying for African agriculture for several reasons. First, the region already faces significant challenges in agricultural resource allocation due to incomplete factor markets and weak property rights institutions. The finding that temperature shocks amplify these existing distortions suggests that climate change could further undermine efforts to improve agricultural productivity through better resource allocation. Second, these results imply that the economic costs of climate change in African agriculture extend beyond the direct effects on crop yields that are typically studied. By disrupting the efficient allocation of land and capital across farms, higher temperatures create additional productivity losses through misallocation channels. This is especially consequential given that agriculture employs about 65-70% of the region's labor force and contributes 30-40% of GDP in many countries. As climate projections indicate that SSA will experience temperature increases above the global mean(IPCC, 2022b), these findings suggest an urgent need for policies that address market failures to improve farmers' adaptive capacity to handle temperature shocks.

Next, I confirm that these results are robust to additional empirical specifications. First, a potential empirical concern with the baseline specification Equation 2.7 is that clustered standard errors may not robustly account for spatial correlation in the error term. To address this plausible concern, I replicate the baseline results by computing the spatial HAC standard errors proposed in Conley (1999) at various distance cutoffs and time lags. The results in Table A2.4 are quantitatively the same. Second, given that the effects of temperature are plausibly not limited to the growing season, I re-estimate Equation 2.7 using the share of days in the four temperature bins in a year. The results summarized in Table A2.5 are robust to this specification as well. Third, I test the robustness of the results using an alternative measure of the outcome variable. Here, I estimate Equation 2.7 using distortion measures under counterfactual efficient allocation as outcome variables. As expected, the results in Table A2.6 confirm that higher temperatures shift households away from efficient allocation. Finally, the results (Table A2.7) are not sensitive to omitting the $\leq 20°$C bin as an alternative way to account for multicollinearity.

2.3.2 The Role of Land Property Rights

In this sub-section, I present and discuss the results of estimating Equation 2.8. The results are summarized in Table 2.4. For brevity, I only present coefficient estimates for the higher temperature bin — above 30°C — and the interaction term. Each column represents results from a separate estimation of Equation 2.8 with varying definitions of the dummy variable of land property rights used in the interaction term. In column (1), I define the property rights to land as a dummy variable which takes the value of 1 if the plot was acquired free of charge. In column (2), the land property right takes the value of 1 if the operated plot is titled or has any other legal document. In column (3), I define land property right as whether the operated plot can be left fallow and in column (4) whether the plot can be sold or used as collateral. Finally, in column (5), I define land tenure security at the village level which takes the value of 1 if the village has a village land certificate following the ratification of the Village Land Act (1999) in Tanzania.

In all three panels, the coefficients in the first row are positive and statistically significant, consistent with the earlier findings in Table 2.3 that high temperatures increase household misallocation of production resources. Regarding the role of property rights to land, the results in panel A show that, although statistically insignificant, land parcels acquired free of charge are associated with higher TFPR dispersion in the presence of high temperatures. However, as revealed in columns (2) – (4), secure private property rights to land decrease the aggregate misallocation due to higher temperatures. The results in panel B provide plausible evidence that the effects of secure private land property rights operate through their important role in reducing temperature-driven land misallocation. More specifically, for households whose land is titled or has any legal document, can be left fallow and can be sold or used as collateral, a percentage increase in growing season days above 30°C relative to a one percentage point increase in growing season days between 20-25°C reduces land misallocation by 0.9%, 0.8%, and 0.8%, respectively. Relative to the mean share of days with an average daily temperature of at least 30° C during the growing season, these effects translate to approximately 13.5%, 12%, and 12%, respectively. However, it is important to note that the coefficient on the interaction term in the last column of panel B is negative, but statistically insignificant. This finding suggests that communal (village-level) land property rights are likely weak and do not offer strong tenure security, particularly land use rights, as shown in Appendix Table A2.8, emphasizing the importance of private property rights to land.

These findings provide compelling evidence on the crucial role of secure private property rights in mitigating temperature-induced resource misallocation in agriculture. The differential effects between private and communal land rights are partic-

Table 2.4. Temperature, Land Property Rights, and Misallocation

	(1)	(2)	(3)	(4)	(5)
Panel A: Log TFPR					
Pct.days $\geq 30°C$	0.021***	0.024***	0.023***	0.023***	0.024***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)
Right $\times$ (Pct.days$\geq 30°C$)	0.001	-0.006**	-0.006*	-0.005*	-0.008
	(0.005)	(0.003)	(0.003)	(0.003)	(0.011)
R^2	0.908	0.908	0.908	0.908	0.908
Panel B: Log MPLa					
Pct.days $\geq 30°C$	0.024***	0.028***	0.028***	0.028***	0.027**
	(0.009)	(0.010)	(0.010)	(0.010)	(0.012)
Right $\times$ (Pct.days$\geq 30°C$)	0.003	-0.009**	-0.008**	-0.008**	-0.004
	(0.006)	(0.003)	(0.003)	(0.004)	(0.017)
R^2	0.877	0.877	0.877	0.877	0.877
Panel B: Log MPK					
Pct.days $\geq 30°C$	0.022**	0.020**	0.020**	0.020**	0.022*
	(0.009)	(0.010)	(0.010)	(0.010)	(0.013)
Right $\times$ (Pct.days$\geq 30°C$)	-0.005	0.002	0.001	0.001	-0.003
	(0.003)	(0.006)	(0.006)	(0.006)	(0.014)
R^2	0.842	0.842	0.842	0.842	0.842
Controls	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Plot FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	11615	11615	11615	11615	11615

Notes: All regressions include the share of growing season days in the $\leq 20°C$ and the $>20\leq 25°C$ temperature bins. The controls include rainfall, age, gender, and education of the head of household and household size. Robust standard errors clustered at the village level in parentheses *** p<0.01, ** p<0.05, * p<0.10.

ularly revealing. While plots acquired without formal rights show increased distortions under high temperatures (though not statistically significant), those with secure private property rights — whether through formal titles, legal documentation, fallow rights, or collateral use rights — demonstrate significantly lower misallocation. Specifically, the reduction in land misallocation by 0.8-0.9% for each percentage point increase in high-temperature days suggests that secure property rights serve as an important institutional buffer against climate-induced market distortions. The ineffectiveness of communal rights in providing similar protection underscores the specific importance of private, formal tenure security in facilitating efficient resource allocation under climate stress.

These results are in line with the literature on the positive link between land property rights and resource allocation, which is comprehensively summarized in Galiani and Schargrodsky (2011). The findings are also consistent with recent evidence that policy reforms that improve land tenure security can address land misallocation by promoting redistribution of land among farmers relative to their productivity. For instance, Zhang et al. (2023) show that a land lease reform increases TFP by reducing farmland misallocation among rice farmers in China. Gai et al. (2020), Chari et al. (2021), and Gao et al. (2021) also find that land certification and land contracting law lead to efficient land reallocation in China. In Africa, Chen et al. (2022) exploit a spatial and temporal variation from a land certification reform in Ethiopia to empirically and quantitatively show that land certification facilitates land reallocation and improves agricultural productivity. In addition, Manysheva (2022) find that a reform that emphasizes land privatization in Tanzania significantly improves resource allocation and economic efficiency.

2.3.3 Additional Results

The results thus far show that higher temperatures amplify pre-existing misallocation. An important question remains: What are the underlying mechanisms behind this misallocation, and how do higher temperatures amplify these mechanisms? Under efficient allocation, we would expect resources to be allocated towards the most productive households, especially in the presence of weather shocks. In other words, we would expect the most productive households to operate more land (either own or rented), and use more capital, and more likely to use intermediate inputs such as organic and chemical fertilizers and pesticides. Furthermore, we would expect these most productive households to have a higher land reallocation potential — the ratio between the efficient to actual size of operated land — in the presence of weather shocks. I hypothesize that these predictions may not hold in the presence of inefficient allocations. To test this theory, I estimate the following regression specification:

$$M_{ihv(d)t} = \sigma TFP_h + \rho(TFP_h \times T^{30}_{v(d)t}) + \alpha W_{v(d)t} + \gamma X_{hv(d)t} + \varphi_v + \mu_t + \epsilon_{hv(d)t} \qquad (2.9)$$

Where $M_{ihv(d)t}$ is the outcome variable of interest. *TFP*$_h$ is the household farming ability — permanent TFP — that does not change over time. $W_{v(d)t}$ includes the weather variables in the growing season: the three temperature bins and the average monthly rainfall, while $X_{hv(d)t}$ are household controls that include gender, age and years of schooling of the head of household and the size of the household. Unlike in Equation 2.7, I control for the village the fixed effects φ_v because the permanent TFP of the household would otherwise be absorbed by the household or plot fixed effects. μ_t accounts for survey year fixed effects. The outcome variable $M_{ihv(d)t}$ is defined in five different ways. First, dummy variables taking the value of 1 if a household used intermediate inputs on the operated plot and whether the plot was rented in, respectively. Third and fourth, the logarithms of the share of land (plot) allocated to crop production and the value of capital, respectively. Finally, as the absolute value of the logarithmic measure of land reallocation potential. The results are summarized in Table 2.5

Table 2.5. Household TFP, Resource Use, and Reallocation Potential

	Intermediate Inputs	Rent-in Land	Log Land	Log Capital	Reallocation Potential
LogTFP	0.003	0.006***	-0.038***	-0.061***	-0.637***
	(0.004)	(0.002)	(0.007)	(0.013)	(0.015)
LogTFP $\times$(Pct.days$\geq 30°$C)	0.000	-0.000*	-0.001	0.002	-0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
Household Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	11615	11615	11615	11615	11605
R^2	0.316	0.120	0.491	0.494	0.567

Notes: The controls include weather variables: the three temperature bins and rainfall; and household variables: age, gender, and education of the head of household and household size. Robust standard errors clustered at the village level in parentheses.
*** p$<$0.01, ** p$<$0.05, * p$<$0.10.

The results provide important additional insights about the potential underlying mechanisms. First, contrary to theoretical expectations, I do not find any evidence that most productive farmers are using more intermediate inputs: fertilizers and pesticides, even in the presence of severe temperatures. Second, while more productive farmers are generally more likely to rent land, this inclination starts to decline for every additional percentage increase in the number of days with an average temperature above 30°C during the growing season. Third, in fact, resources are not allocated to the most productive farmers, including during periods with severe temperature. In particular, the association between TFP and the share of land and the value of capital used in crop production is negative and statistically significant at 1%. Furthermore, land reallocation potential is decreasing among high-productive farmers. Together, these findings point to the presence of factor market frictions that lead to the overall observed misallocation.

2.4 Conclusion

This paper investigates how temperature shocks affect agricultural resource allocation in SSA, with a particular focus on Tanzania. By combining detailed plot-level production data with high-resolution satellite weather information, the study provides novel evidence on the relationship between severe temperature fluctuations and factor misallocation in agriculture, while also examining how land property rights might mitigate these weather-induced distortions. This analysis is particularly relevant given

SSA's vulnerability to climate change and the region's persistent challenges with agricultural productivity.

Empirical analysis reveals that exposure to high temperatures significantly exacerbates resource misallocation in agriculture. Specifically, a one percentage point increase in the number of growing season days with temperatures above 30°C is associated with increases in aggregate misallocation by 2.2%, driven by increases in land and capital misallocation of 2.5% and 2.1%, respectively. These effects are economically substantial — a 15% increase in hot days during the growing season leads to approximately 33% higher aggregate misallocation. The analysis further demonstrates that secure private property rights to land can help mitigate these temperature-driven distortions. However, village-level communal land rights appear insufficient to protect against such weather-induced misallocation, highlighting the specific importance of private tenure security. Further evidence suggests that these misallocations persist because resources are not flowing to the most productive farmers, even during periods of severe temperature stress, pointing to significant factor market frictions.

These findings have profound implications for agricultural policy in SSA, particularly as the region faces increasing threats from climate change. First, they suggest that rising temperatures could further deteriorate agricultural productivity not only through direct biological effects on crops but also indirectly through worsened resource allocation. This double impact makes it crucial for policymakers to consider both adaptation strategies and institutional reforms. Second, the results emphasize that land reform policies promoting secure private property rights could serve as an effective adaptation strategy against climate-related productivity losses. However, the findings also indicate that traditional communal land rights systems, while culturally important, may need to be complemented with stronger individual tenure security to build climate resilience. This suggests a need for carefully designed land reforms that balance individual property rights with existing communal systems.

Several important questions emerge from this study that warrant future research attention. First, there is a critical need to understand how temperature-driven misallocation might differentially affect male and female farmers, particularly given existing gender inequalities in agricultural resource access. Second, future research should examine how ongoing institutional reforms in land and credit markets might interact with weather-induced misallocation - for instance, how different types of land reforms or financial innovations might help or hinder adaptation to temperature stress. Third, quantifying the potential productivity gains from addressing weather-induced misallocation would provide valuable insights for policy prioritization. Finally, researchers should investigate whether similar patterns of weather-induced misallocation exist in other SSA countries with different institutional arrangements and climate conditions. Such comparative analysis could help identify best practices for institutional design in the face of climate change.

Essay 3

Human Capital, Climate Beliefs, and On-farm Adaptation to Climate Change in Ethiopia

Abstract

Human capital accumulation through increased education attainment plays a crucial role in the global response to climate change, yet causal evidence directly linking education to adaptation in agriculture remains scarce. In this paper, I study the causal effects of formal education on on-farm adaptation to climate change in Ethiopia. To achieve this, I employ an instrumental variable (IV) design that exploits spatio-temporal variation in exposure to a policy–induced natural experiment — the introduction of free primary education (FPE) in 1995 in Ethiopia — as an instrument for formal education. I find that an additional year of formal education significantly increases farmers' probability of investing in irrigation and soil fertility and improved seed technologies, as well as practicing conservation agriculture, particularly crop rotation, minimum tillage, and managing soil erosion. I further show that education's role extends beyond technology adoption to enhanced risk management capabilities, with educated farmers better preventing crop damage, reducing post-harvest losses, and showing greater capacity for income diversification and self-sufficiency. Consistent with these adaptation outcomes, I find that formal education fosters greater awareness of climate change threats and stronger beliefs in the necessity of climate action, with educated individuals more likely to support environmental protection measures and recognize the shared responsibility of citizens, government, and industry in addressing climate challenges. These findings demonstrate how education builds climate resilience through multiple channels, underscoring the crucial role of human capital accumulation in climate adaptation.

Key Words: Human Capital, Education, Climate Change Adaptation, Africa.
JEL Classification: I25, I26, Q10, Q54

3.1 Introduction

The accelerating pace of climate change poses significant threats to global agricultural systems, with disproportionate impacts on regions already vulnerable due to socioeconomic and environmental challenges (Hallegatte and Rozenberg, 2017; King and Harrington, 2018; Diffenbaugh and Burke, 2019; Paglialunga et al., 2022). Among these, sub-Saharan Africa (SSA) faces some of the most severe threats, with millions of smallholder farmers grappling with unpredictable weather patterns, changing growing seasons, and an increased frequency of extreme weather shocks (IPCC, 2022a). As these challenges mount, the need for effective adaptation strategies becomes increasingly urgent. Yet, the capacity of farmers to respond effectively to these changes depends not only on access to adequate resources but also on their ability to comprehend the magnitude of climate threats and recognize the long-term benefits of adopting sustainable farming practices and technologies.

Human capital plays a crucial role in the global response to climate change by equipping people with the knowledge and skills necessary to understand and address its multifaceted impacts. Education, a fundamental component of human capital, fosters the development of skills, increases awareness of environmental issues, and encourages the development of climate–friendly behaviors, beliefs, and attitudes (Angrist et al., 2024). These, in turn, can drive support for climate-friendly policies and the adoption of sustainable farming practices, particularly in agricultural communities where adaptation is essential for survival. Therefore, the development of human capital is not only a means of reducing vulnerability to climate change, but also a catalyst for proactive engagement in climate mitigation and adaptation efforts, such as the adoption of climate–smart agriculture (CSA) practices and technologies. Despite this crucial role, empirical evidence that examines the causal effects of human capital accumulation on climate adaptation in agriculture remains scarce, particularly in SSA despite a sharp increase in schooling rates in the region in the last three decades (Majgaard and Mingat, 2012).

In this paper, I study the effects of formal education attainment on on-farm adaptation to climate change in Ethiopia, a country emblematic of the broader challenges faced by SSA[1]. To motivate the study's main objective, I first analyze the non-causal relationship between formal schooling and the awareness of the Ethiopian public about climate change, attitudes toward, and preferences for climate and environmental action. Next, I exploit region–by–cohort variation in exposure to the potential impact of FPE as a plausibly valid instrument for individuals' years of education to estimate the causal effects of formal education on on–farm adaptation to climate change. Ethiopia provides a unique and relevant setting for studying the role of education in climate adaptation because the introduction of FPE in 1995 coincides with a period marked by an increase in frequency and intensity of extreme weather events, particularly droughts and floods (Viste et al., 2013; Mekonen et al., 2020).

I have two main results. First, consistent with Fagan and Huang (2019), I find descriptive evidence that human capital influences public awareness of climate change and fosters beliefs in climate action. In particular, I find that individuals who have completed at least primary school education are more aware of climate change and its economic threats. Furthermore, more educated individuals are more likely to believe that ordinary citizens, the private sector (industry), and the government all have

[1] `https://climateknowledgeportal.worldbank.org/country/ethiopia/vulnerability`

a primary responsibility in limiting climate change and that the government should impose strict regulations to limit exploitation of natural resources. Second, my main IV results reveal that higher education attainment increases the farmers' likelihood of adopting CSA practices. In particular, an additional year of formal education increases the probability of practicing conservation agriculture, particularly crop rotation, minimum tillage and preventing erosion by 12.7, 6.7 and 10.1 percentage points, respectively. Similarly, the probability of investing in improved seed and irrigation increases by 2.3 and 2.5 percentage points, respectively. Beyond on-farm adaptation, I find that well educated farmers have more adaptive capacity and resilience through better post-harvest loss management and increased job diversification and self-sufficiency.

The role of education in the adoption of agricultural technology has long been recognized in the literature. Studies have established that education improves farmers' ability to process information, evaluate new technologies, and adapt to changing production environments (O'Donoghue and Heanue, 2018; Abdulai and Huffman, 2014). However, much of this literature has focused on establishing correlations between educational attainment and adoption of productivity-enhancing technologies, with limited comprehensive attention to climate-resilient practices. In addition, these studies often face empirical challenges in establishing causality due to the endogenous nature of education attainment. While a growing body of experimental studies has examined causal effects through training interventions and agricultural extension programs (Pan et al., 2018; Van Campenhout et al., 2018; Larochelle et al., 2019; Shikuku et al., 2019; Yitayew et al., 2021), these approaches have important limitations. Such interventions are typically closely monitored, context-specific, and often short-term in nature, potentially limiting their external validity and ability to inform broader policy on human capital development.

This paper is also related to the growing literature on the economic returns of FPE in SSA. Several studies show that FPE has positive effects on school enrollment and completion rates, particularly for students from disadvantaged backgrounds in Kenya and Ethiopia (Lucas and Mbiti, 2012; Chicoine, 2019). Beyond educational outcomes, studies have documented the impacts of FPE on various socioeconomic dimensions. In Ethiopia, FPE led to increased literacy and health knowledge (Chicoine, 2019). In Nigeria, universal primary education reduced early childbirth (Osili and Long, 2008) and there is evidence on modest impacts on income (Oyelere, 2010) and increased political participation (Larreguy and Marshall, 2017). More recent evidence shows the positive effects of FPE on financial inclusion in Kenya (Ajayi and Ross, 2020).

This study advances these two strands of literature in several important ways. First, by exploiting quasi-experimental variation in education access through a nationwide policy reform, I provide credible causal evidence linking formal education to climate-smart technology adoption. Second, I examine adaptation outcomes comprehensively, from awareness and beliefs to actual adoption behavior and risk management, providing novel insights into the mechanisms through which education enhances adaptive capacity. Third, I demonstrate that education's effects extend beyond simple technology adoption to broader resilience-building through enhanced risk management capabilities and livelihood diversification, suggesting that general human capital accumulation may be more effective at fostering comprehensive climate adaptation than targeted agricultural training programs.

I also contribute to the FPE literature in Africa by examining previously unexplored dimensions of its long-term impacts. While existing studies have focused on health, fertility, and financial outcomes, I provide the first evidence of the role of FPE in building climate resilience through human capital development. Our findings demonstrate how such broad-based educational interventions can have far-reaching effects on communities' ability to adapt to environmental challenges, suggesting an important additional benefit of universal education policies in developing countries.

The rest of the paper proceeds as follows. Section 2 provides a background on education reforms in Ethiopia and introduces the concept of CSA for adaptation to climate change. Section 3 describes the methods: data and summary statistics, construction of the FPE instrument, and the empirical strategy. Section 4 presents and discusses the results, while Section 5 concludes.

3.2 Setting and Background

3.2.1 Education Reforms in Ethiopia

The Ethiopian education system has undergone significant reforms in the past few decades, with the aim of expanding access to schooling and improving educational outcomes. These reforms were implemented on the backdrop of major political and economic transitions in the country.

From 1974 to 1991, Ethiopia was governed under military rule and then by communist leadership. In 1991, a major political shift occurred with the establishment of a federal system that divided the country into nine regions and two city administrations (Ofcansky et al., 1993). This decentralization of power set the stage for changes in the country's education system. Before the reforms, Ethiopia's education system followed a 6-2-4 structure: 6 years of primary school, 2 years of junior secondary and 4 years of senior secondary (World Bank, 2009). Access to education was limited, with low enrollment rates, especially in rural areas. There were also wide disparities in educational access and quality across different regions of the country (World Bank, 2009).

In 1993, the first major education reform came with Proclamation No. 41, which decentralized control of primary and secondary education to the regional level. This was followed in 1994 by the Education and Training Policy (ETP), which introduced two pivotal changes. First, it eliminated school fees for grades 1-10, making primary education free and compulsory. This was aimed at reducing the financial burden on families and increasing access to schooling. Second, it restructured the education system to a 4-4-2-2 model: 4 years of first cycle primary (grades 1-4), 4 years of second cycle primary (grades 5-8), two years of general secondary (grades 9-10), and 2 years of preparatory secondary (grades 11-12) (Oumer, 2009; World Bank, 2009). The official primary school entry age remained at 7 years. National examinations, previously administered at the end of each school cycle, were now administered only at the end of grade 8 and grade 10. These reforms led to a substantial increase in primary school enrollment, particularly in grade 1 as shown in **??**. Overall, primary enrollment nearly doubled between 1994 and 2000. Studies have found that reform increased the average years of completed schooling and improved some educational outcomes. For instance, Chicoine (2016) estimated that the reform increased schooling by more than a full year, increased grade 8 exam pass rates, and increased literacy by almost 10%.

In conclusion, the education reforms of the 1990s laid an important foundation for Ethiopia's efforts to expand access to schooling and develop its human capital.

While issues of educational quality remain, the policies helped bring primary education within reach for many more Ethiopian children. Ongoing research continues to examine the long-term impacts of these reforms on educational attainment, economic outcomes, and social development in Ethiopia. This paper exploits the geographical and temporal variation of the potential impact of the FPE policy reform as an instrument for formal education to estimate the impacts of schooling on on-farm adaptation to climate change in Ethiopia.

3.2.2 Climate-Smart Agriculture

This study focuses on climate adaptation strategies that are consistent with the concept of CSA. According to FAO (2013) and Lipper et al. (2014), CSA is an approach to transforming and reorganizing agriculture under the new realities of climate change to sustainably increase productivity, enhance adaptation, and reduce greenhouse gases (GHGs) (i.e., mitigation) with the main goal of improving food security and reducing poverty.

In a comprehensive systematic review, Rosenstock et al. (2016) outline the specific farm-level practices that are consistent with CSA. In crop farming, CSA encompasses a wide range of techniques to improve soil health, water management, and crop resilience. Conservation agriculture is a key approach that combines reduced soil disturbance, crop rotation, and continuous soil cover. Second, soil amendments play a crucial role, including the use of organic fertilizers — compost, manure, green manure, biochar — and integrated soil fertility management. Third, precision agriculture techniques such as microdosing, fertilizer banding, and subsurface fertilization aim to optimize nutrient application. Crop management and tillage practices are another important CSA strategy. Crop management practices include diverse crop rotations, intercropping (especially with legumes), and mulching. Tillage practices range from reduced till to zero-tillage systems. The use of improved crop varieties tolerant to heat and salinity is further emphasized to improve resilience to climate stresses. In addition, water management techniques for upland soils include drip irrigation, water harvesting, deficit irrigation, and the use of watersheds. Lastly, agroforestry, a farming system that integrates trees with crops and livestock, plays an important role in enhancing biodiversity, improving soil health, and sequestering carbon, thus increasing farm resilience to climate change and contributing to climate mitigation. Collectively, these agronomic CSA practices aim to improve soil health, water use efficiency, and crop productivity while enhancing resilience to climate variability and reducing greenhouse gas emissions where possible (Lipper et al., 2017).

In Ethiopia, Jirata et al. (2016) and Eshete et al. (2020) reveal that farmers implement several CSA practices. These include conservation agriculture, particularly reduced tillage and crop rotation; integrated soil fertility management using compost and efficient fertilizer application; small-scale irrigation for year-round cropping; and agroforestry combining traditional and improved practices. Other key approaches involve crop diversification with drought-tolerant (improved) varieties, improved livestock management practices, water conservation techniques, and the adoption of alternative energy sources. In addition, farmers are implementing post-harvest technologies and diversifying livelihoods through activities such as apiculture and aquaculture to improve resilience to climate challenges.

3.3 Methodology

3.3.1 Data

I use individual-level data from three main sources. First, information on over 5 million individuals from the 1994 Ethiopian census data collected by the Ethiopian Central Statistical Agency. This data is made publicly available by the Minnesota Population Center as part of the Integrated Public Use Microdata Series (IPUMS) International. Following Lucas and Mbiti (2012) and Chicoine (2019), I use the data source to calculate the potential impact of FPE for each region using schooling rates at the region level prior to the introduction of FPE , which I discuss in subsection 3.3.2.

The second data source is the 8th and 9th rounds of Afrobarometer surveys that were implemented in 2020 and 2023, with sample sizes of 2,378 and 2,400 respondents, respectively. These surveys collect detailed information of public attitudes and opinions on democracy, governance, and other development topics, including climate change and the environment, from 35 African countries. I generate a series of important variables on the individual's awareness, attitudes, and beliefs about climate change, pollution, and the role of government, the private sector, and private citizens on climate action. Two dummy variables taking the value of one on climate change awareness in both rounds are measured based on two questions:"Have you heard about climate change?" and "Do you think climate change is making life in Ethiopia better or worse?" Next, questions on pollution and climate action are only asked in the 9th round. I use these questions to generate a series of dummy variables on whether individuals agree with the following statements: (i) pollution is a problem in my community; (ii) plastic bags are a major source of pollution in my community; (iii) deforestation is an important environmental issue. Third, using the 9th round, I generate dummy variables that measure public beliefs and attitudes toward climate and environmental action. These are: (i) the government should do much more to limit pollution; (ii) ordinary citizens have a primary responsibility to reduce pollution; (ii) the private sector has a primary responsibility to reduce pollution; (iii) citizens can help limit climate change; (iv) the government must act now to limit climate change; and (v) the private sector must act now to limit climate change. Lastly, I observe information on the age, gender, and education of the respondent. However, one limitation of the Afrobarometer is that it does not report the actual individual years of schooling, but rather the level of education. Given this challenge, I generate a dummy variable taking the value of 1 if the individual has at least completed primary school. The intuition here is that individuals who had full exposure to the FPE policy were more likely to complete primary school.

The third data source is the five waves of nationally representative surveys[2] with a sample size of 45,874 observations from the Ethiopia Socioeconomic Panel Surveys (ESPS), a collaborative project between Ethiopia's Statistical Service (ESS) and the World Bank's Living Standards Measurement Study-Integrated Agriculture Surveys (LSMS-ISA) project. I use these data to construct important variables with information on individuals and the adoption of CSA practices at the plot level. First, I identify the main decision maker on farming practices for each household plot. Second, using information from the household questionnaire, I generate variables for the gender, age, and years of formal schooling of the main decision maker for each household plot (ie, plot manager). Third, from the agriculture post-planting and post-harvest

[2]The 5 survey rounds were conducted in 2011-12, 2012-13, 2014-15, 2019-20 and 2021-22, respectively.

questionnaires, I generate a series of variables on different farming practices that are consistent with the concept of CSA, crop damage and post-harvest loss management. In particular, I generate dummy variables to determine whether the decision maker: (i) uses soil fertility methods defined as the use of organic fertilizers such as compost, covering field with crop residue, manure and chemical fertilizers; (ii) practices crop rotation; (iii) practices mixed cropping; (iv) use of improved versus traditional seed; (v) manages soil erosion[3] ; (vi) uses irrigation; and (vii) practices minimum tillage[4]. I also observe information on whether the plot decision makers suffered crop damage, the causes of the damage and whether efforts were made to prevent crop damage on each operated plot, as well as if an individual suffered post-harvest losses.

3.3.2 Measurement of FPE Impact as Instrument

Following the same approach as in Chicoine (2019), I use the 1994 Ethiopian census data from IPUMS to calculate the magnitude of the potential impact of FPE for each region in Ethiopia. As noted in Lucas and Mbiti (2012), the impact of eliminating school fees is expected to be greater in regions with lower pre-reform primary school completion rates relative to regions that already had high completion rates.

Given that primary school comprises grades 1–10, the underlying mechanism is that for every region, r, there is some fraction of individuals who never attended school. This group has a maximum potential benefit of 10 years of additional schooling due to FPE. Similarly, for each of grades 1–9 in each region, there exists some fraction of students who would have dropped out after completing that grade. These students who would have dropped out after each successive grade from 1 to 9 could gain progressively fewer additional years, ranging from 9 years for 1st grade dropouts to 1 year for 9th grade dropouts. Those who had completed 10 or more years are assumed unaffected. Therefore, the maximum potential impact of eliminating school fees in region r for those who never attended school is the product of the fraction of students who never attended school in that region and the maximum ten years of additional schooling for this group. The same applies to those who would have dropped out at each successive grade. The maximum potential impact of the reform in region r is calculated by summing these impacts in grades 0 through 9 and can be formalized as follows:

$$FPE_r = \sum_{g=0}^{9}(10-g)F_{r,g} \tag{3.1}$$

Where r and g represent region and grade, respectively. $F_{r,g}$ are the fractions of students in a given region who never attended school or who would have dropped out for each successive grade 1 through 9. Thus, FPE_r is the effective impact of the introduction of FPE in each region. This impact is interpreted as the number of additional years of schooling generated in each region r due to FPE, relative to the level of primary school completion of the pre-reform cohorts (Chicoine, 2019).

[3]Soil erosion management takes the value of 1 if an individual adopts soil erosion prevention strategies such as terracing, contour ploughing, plating cover crops and use of water catchments with the main goal of managing soil erosion

[4]Given that the surveys report the number of times farmers tilled their land in the current agricultural season, I define minimum tillage as a dummy variable taking the value of 1 if the number of land tillage times is less or equal to 1.

However, notice that FPE_r generated from Equation 3.1 only varies geographically across regions, and, therefore, does not capture the variation in policy exposure across years. In other words, Equation 3.1 assumes that every primary school student in a given region *r* is exposed to the same impact regardless of their age (year of birth). The formal school starting age in Ethiopia is 7 years. Therefore, given that FPE was introduced in 1995, it follows that assuming full compliance with the school starting age, only students born in 1987 or later could potentially receive the full 10 years of exposure to FPE, and thus maximum impact FPE_r. This also implies that individuals born in 1986 will have completed grade 1 by the time FPE is introduced, and therefore only have 9 years of FPE at their disposal. This pattern continues until the 1977 birth cohort, as individuals from this birth year or earlier would have finished their entire ten-year schooling before 1995. Given this context, I modify Equation 3.1 to capture both the geographic and temporal variation in the impact of the FPE generated by the pre-reform levels of primary schooling in each region, and the year of birth follows:

$$FPE_{ry} = \begin{cases} \sum_{g=0}^{9} (10-g) \cdot F_{r,g} & \text{if } y \geq 1987 \\ \sum_{g=(1987-y)}^{9} (10-g) \cdot F_{r,g} & \text{if } 1978 \leq y \leq 1986 \\ 0 & \text{if } y \leq 1977 \end{cases} \tag{3.2}$$

In Equation 3.2, FPE_{ry} now measures the impact of FPE that varies across regions and age cohort. I calculate FPE_{ry} using the 1994 schooling rates census sample of individuals who were at least five years old when FPE was introduced, born between 1970–1990.

3.3.3 Empirical Strategy

To motivate my main analysis, I first assess the association between schooling and awareness of climate change and attitudes toward climate action using Afrobarometer surveys. To achieve this, I specify and estimate the following regression model.

$$C_{idt} = \beta Education_{idt} + \gamma X_{idt} + \delta_d + \theta_t + \epsilon_{idt} \tag{3.3}$$

Where *i*, *d*, and *t* index individual, district, and survey year, respectively. C_{idt} represents different sets of outcome variables, namely, awareness of climate change and its threats, belief and awareness of the threat of pollution, and attitudes towards climate action by the government, the private sector, and the private citizens. Given that the Afrobarometer surveys code the education of the respondent in a range of 0 to 9 where 0 means no formal education and 9 represents postgraduate education, I define the main explanatory variable of interest $Education_{idt}$, as a dummy equals one in three different ways: if an individual has (i) completed primary school; (ii) post-primary school; and (iii) completed secondary school. I control for individual-level characteristics X_{idt} that include the age and gender of the respondent and an indicator of whether the individual is from a rural or urban area. I also include district fixed effects σ_d and year fixed effects θ_t for regressions that use the two survey rounds. The parameter estimate of interest β measures the correlation between primary school completion and the outcome variables.

Next, leveraging detailed plot-level crop farming data from LSMS-ISA, I set out to estimate the causal effects of formal education on on-farm adaptation to climate change using the following baseline regression specification.

$$Y_{icrt} = \alpha \mathit{Education}_{icrt} + \gamma X_{icrt} + \delta Trend_{rt} + \sigma_c + \sigma_r + \epsilon_{irct} \tag{3.4}$$

Where *i, c, r* and *t* index individual plot manager, age cohort, region and survey year, respectively. Y_{irct} is a dummy variable that takes the value of 1 if the plot manager adopts a CSA practice in survey year *t*. I focus on nine CSA practices that are reported in the plot-level surveys: Use of soil fertility methods, mixed cropping, crop rotation, improved seed, use of pesticides, participation in farm-level extension programs, erosion prevention, irrigation, and minimum tillage. The main explanatory variable $\mathit{Education}_{icrt}$ is defined as the number of years of formal education of the individual. X_{icrt} is a vector of individual-level covariates that include gender while Trend_{rt} is region-specific linear time trends that capture how outcomes evolve differently over time in each region. I include each cohort (σ_c) and region (σ_r) fixed effects to account for potential yearly changes across Ethiopia and time-invariant differences between regions that potentially influence schooling, respectively. I account for within-region correlation by clustering the standard errors at the region. Given that there was a reset in the LSMS-ISA survey sampling frame between the first three and last two waves, I follow Chicoine (2019) and Ajayi and Ross (2020) to weight the estimates using the survey sampling weights provided. The baseline includes individuals born between 1970 to 1989 — the last fully pre–reform cohorts and the first three fully post–reform cohorts, relative to the formal school starting age of seven. This implies that the youngest person in the baseline analysis is presently 35 years old.

However, the parameter α does not identify the causal effect of schooling for several plausible reasons. First, the problem of endogeneity resulting from the potential correlation between years of formal education and both observable and unobservable factors that influence farming decisions (outcomes). For instance, an individual's age, gender, and economic status can influence both their education access and farming decisions. In other words, years of formal education are not randomly assigned. Second, the problem of reverse causality. Individuals who believe and accept the realities of climate change may opt for higher levels of education to enhance their adaptation ability.

To address these identification challenges, I employ the fixed effects instrumental variable (IV) approach that exploits geographical and temporal variation in the potential region-level impact of the FPE FPE_{ry} generated from the pre-reform levels of primary schooling in each region by age cohorts discussed in subsection 3.3.2 as an instrument for individual's years of formal education. This instrument is plausibly valid for two important reasons. First, individuals cannot choose their year of birth. Therefore, using the impact of FPE that varies across regions and and age cohorts implies that FPE_{ry} is exogenous and as good as randomly assigned. Second, while the IV exclusion assumption is not directly testable (Angrist and Pischke, 2009), it is intuitive that FPE_{ry} does not directly influence the current agricultural decisions of individuals (and households) except through the development of their human capital. In fact, Chicoine (2019) finds that literacy rates, access to family planning information, HIV knowledge, and knowledge of the location of HIV testing increased in Ethiopia due to an increase in the years of formal education of individuals as a result of increased exposure to the FPE.

In light of this, I estimate the causal effects of education on on-farm adoption of CSA practices using the IV framework in two stages as follows.

$$1^{st}\text{ stage:}\quad \textit{Education}_{irct} = \varphi FPE_{ry} + \gamma X_{irct} + \delta Trend_{rt} + \sigma_c + \sigma_r + \epsilon_{irct} \tag{3.5}$$

$$2^{nd}\text{ stage:}\quad Y_{irct} = \alpha \widehat{Education}_{irct} + \gamma X_{irct} + \delta Trend_{rt} + \sigma_c + \sigma_r + \epsilon_{irct} \tag{3.6}$$

Where the 1^{st} stage uses a difference-in-differences[5] strategy to estimate the effects of the potential impact of the FPE on the years of formal education of an individual. The predicted years of formal education from 1^{st} stage are then used in Equation 3.6 to isolate the causal effects of human capital on the outcome variables in the 2^{nd} stage. The controls are as defined in Equation 3.4. Under the standard assumptions for a valid IV, the estimate α identifies the effect of an additional year of formal education on the probability of adopting on-farm CSA strategies.

3.4 Results and Discussion

3.4.1 Summary Statistics

The LSMS-ISA information is summarized in Table 3.1. The demographic profile of the sample reveals that the average age is approximately 35 years, with a notably low proportion of female respondents at 12%. Education attainment, measured in years of formal education, averages about 2.8 years, indicating relatively low overall educational levels in Ethiopia.

Table 3.1. Summary Statistics: LSMS-ISA

	N	Mean	SD
Age	45874	35.274	6.705
Female	45874	0.120	0.325
Education (years)	45874	2.775	3.574
Use fertility methods	45874	0.499	0.500
Practice mixed cropping	45874	0.221	0.415
Practice crop rotation	45874	0.239	0.427
Use improved seed	45874	0.074	0.261
Use pesticides	45874	0.121	0.326
Use irrigation	45874	0.039	0.194
Prevent soil erosion	45874	0.428	0.495
Practice minimum tillage	45874	0.191	0.393
Suffered cop damage (general)	45874	0.452	0.498
Suffered cop damage (weather risks)	45874	0.339	0.473
Prevented damage	45874	0.351	0.477

[5] The 1^{st} stage is a variant of difference-in-differences with continuous treatment that compares schooling rates across regions by age-cohorts: $\textit{Education}_{irct} = \varphi(\sum_{c\leq'77}^{\geq'87} \text{Cohort}_c \times FPE_r) + \gamma X_{irct} + \delta Trend_{rt} + \sigma_c + \sigma_r + \epsilon_{irct}$

Regarding the adoption of CSA practices, I observe varying adoption rates that paint an interesting picture of agricultural practices in Ethiopia. Soil fertility management, particularly defined as collective use of organic fertilizers such as compost, covering field with crop residue, manure and chemical fertilizers show substantial adoption, with 50% of the farmers incorporating these practices into their agricultural operations. Soil erosion prevention defined here as adoption of strategies such as terracing, contour ploughing, plating cover crops and use of water catchments with the main goal of managing soil erosion, is adopted by about 43% of the respondents, while mixed cropping and crop rotation are practiced by about 22% and 24% of the farmers, respectively, indicating moderate adoption of these sustainable farming techniques.

However, more technologically advanced or resource-intensive practices show notably lower adoption rates. Only 7.4% of the respondents report using improved seed technologies, Irrigation, crucial for climate resilience, are implemented by only 4% of the respondents. Minimum tillage, another important conservation agriculture practice, is adopted by 19% of the farmers. These statistics reveal a significant gap in the adoption of modern agricultural technologies and practices.

The data also provide information on the farmers experience with crop losses. In particular, 45.2% reported experiencing crop damage out of which 34% attributed this damage to weather related risks — excessive rain, droughts, hail, frost, and flood — while 35% implemented damage prevention measures. These statistics highlight potential areas for intervention to improve the adoption of CSA practices for enhanced adaptation and resilience.

The Afrobarometer survey summary statistics presented in Table 3.2, provide information on awareness of climate change and beliefs and attitudes about climate and environmental action. The sample demonstrates a balanced gender representation (50% female) with a mean age of approximately 36 years. Educational attainment, measured by primary school completion, is 40.7%. Notably, less than half of the respondents (45.9%) report being aware of climate change, with only 28.1% perceiving that climate change is negatively impacting their lives. This low awareness contrasts with a higher recognition of specific environmental issues: 64.1% identify pollution as a major problem and 66.3% recognize plastic bags as a significant source of pollution. Regarding climate action beliefs, there is a consistent trend of around 35-40% of respondents believing that various stakeholders (citizens, government, industry) should do more to combat climate change. Interestingly, a higher proportion (52.8%) believe that the government is primarily responsible for the reduction of pollution, compared to 49.2% who assign this responsibility to private citizens. These findings highlight the complex interplay between awareness, responsibility attribution, and potential for action to address the challenges of climate change and environmental threats in SSA.

3.4.2 Motivating Evidence: Schooling and Climate Beliefs

I start by presenting the motivating evidence — correlation between schooling and climate beliefs and attitudes — from estimating Equation 3.3. The results in Table 3.3 summarize the correlation between different levels of education attainment and awareness of climate change and environmental threats. The outcome variables in columns (1) and (2) are dummy variables taking the value of 1 if the respondent has ever heard about climate change and agrees with the statement climate change is making life in Ethiopia worse, respectively. In columns (3)–(5), the outcome variables

Table 3.2. Summary Statistics: Afrobarometer Surveys

	N	Mean	SD
Sociodemographic:			
Age	4778	35.614	27.625
Female	4778	0.500	0.500
Primary school completion	4778	0.407	0.491
Post-primary school	4778	0.288	0.453
Secondary school completion	4778	0.211	0.408
Climate Change and Pollution Awareness:			
Aware of climate change	4778	0.459	0.498
Climate change is making life worse	4778	0.281	0.449
Pollution is a major environmental problem	2400	0.641	0.480
Plastic bags are a major source of pollution	2400	0.663	0.473
Deforestation is an important environmental issue	2400	0.285	0.452
Beliefs in Climate Action:			
Citizens should help limit climate change	2400	0.370	0.483
Government must act now to limit climate change	2400	0.392	0.488
Citizens should do more to fight climate change	2400	0.413	0.493
Industry should do more to fight climate change	2400	0.359	0.480
Government should do more to fight climate change	2400	0.355	0.479
Citizens have primary responsibility to reduce pollution	2400	0.492	0.500
Government has primary responsibility to reduce pollution	2400	0.528	0.499
Natural resource extraction needs more and strict regulation	2400	0.772	0.419

are dummy variables that measure the response's awareness that pollution is a major environmental problem in the community, plastic bags are a major source of pollution in their communities, and deforestation is an important environmental issue, respectively. By including these additional outcome variables, my aim is to demonstrate that education not only raises awareness of climate change, but also promotes understanding of various environmental challenges that potentially contribute to the broader climate crises.

The results robustly reveal a statistically significant correlation between education attainment and awareness of climate change and pollution as an environmental threat. In particular, from columns (1) and (2) of all three education levels, I find that higher education attainment increases the probability that an individual is aware of climate change and that climate change is a major threat to the country's welfare. Second, the coefficients in columns (3) and (4) reveal that there is a higher probability of recognizing pollution as a major threat and plastic bags as a main driver of pollution among individuals who have at least a primary school education. The relationship is robust to higher levels of education (panels B and C). Third, although statistically insignificant, I find a positive correlation between education and the public's belief that deforestation is a major environmental concern. Note that including awareness of environmental threats such as pollution and deforestation in the analysis — columns (3)–(5) —, even though they are not directly synonymous with climate change, strengthens

Table 3.3. Education Attainment and Climate Change Awareness

Aware of:	Climate Change		Environment Threats		
	(1)	(2)	(3)	(4)	(5)
Panel A					
Primary School	0.168***	0.108***	0.082***	0.050**	0.026
	(0.017)	(0.015)	(0.023)	(0.023)	(0.021)
Panel B					
Post-primary	0.205***	0.151***	0.094***	0.069***	0.004
	(0.018)	(0.017)	(0.024)	(0.024)	(0.022)
Panel C					
Secondary School	0.202***	0.143***	0.092***	0.055**	0.015
	(0.020)	(0.019)	(0.025)	(0.026)	(0.023)
Controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No	No
Observations	4778	2193	2400	2400	2400

Notes: Controls include age and gender of the respondent and a dummy indicator for rural. Robust standard errors in parentheses. Columns 1–2 use Afrobarometer rounds 8–9 data, measuring awareness of climate change (1) and belief that it worsens life in Ethiopia (2). Columns 3-5 use round 9 only, indicating respondents' recognition of: general pollution (3), plastic waste (4), and deforestation (5) as major environmental concerns in their communities. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

the robustness of the results. Education likely plays a pivotal role in improving general environmental awareness, which includes understanding climate change and related issues such as pollution and deforestation. By showing that education is associated with increased awareness of these broader environmental issues, we can better argue that the accumulation of human capital fosters a comprehensive understanding of environmental threats. This broader awareness is critical because pollution and deforestation are significant contributors to climate change, and understanding these interconnected issues can lead to more informed and holistic environmental behaviors and attitudes.

Next, I present the correlation between formal education and public preferences and attitudes toward action on climate change and environmental protection in Table 3.4. The outcome variables in columns 1–5 measure public beliefs in climate change action and are defined as dummy variables taking a value of one if the respondent agrees with the following statements, respectively: (i) Citizens can help limit climate change; (ii) the government must act now to limit climate change; (iii) ordinary citizens should do more to fight climate change; (iv) the private sector — the industry — should do more to fight climate change; and (v) the government should do more to fight climate change. The outcome variables in columns (6)–(7), on the other hand, measure public beliefs in actions toward environmental protection, and they are dummy variables taking a value of 1 if the respondent agrees with the following statements, respectively: (i) Ordinary citizens have primary responsibility to reduce

Table 3.4. Education Attainment and Climate Change and Environment Action

Action Toward:	Climate Change					Environment Protection		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A								
Primary School	0.135***	0.159***	0.202***	0.155***	0.163***	0.069***	-0.030	0.036*
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.022)	(0.020)
Panel B								
Post-primary	0.176***	0.190***	0.243***	0.162***	0.193***	0.035	-0.043*	0.078***
	(0.026)	(0.025)	(0.025)	(0.026)	(0.026)	(0.026)	(0.024)	(0.021)
Panel C								
Secondary School	0.162***	0.193***	0.204***	0.140***	0.158***	0.034	-0.039	0.066***
	(0.028)	(0.028)	(0.028)	(0.029)	(0.028)	(0.028)	(0.025)	(0.022)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2400	2400	2400	2400	2400	2400	2400	2400

Notes: Controls include age and gender of the respondent and a dummy indicator for rural. All regressions use the 9^{th} (2023) round of Afrobarometer Surveys.Outcome variables in columns 1-5 are binary indicators (0/1) for respondents' agreement that: citizens can help limit climate change (1), government must act now (2), citizens should do more (3), private sector should do more (4), and government should do more (5) to fight climate change. Columns 6-7 measure environmental protection beliefs: citizens' responsibility to reduce pollution (6) and need for stronger government action on pollution (7). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

pollution; (ii) the government should do much more to limit pollution; and (iii) natural resource extraction needs more and strict regulation.

The results in Table 3.4 show a consistent positive association between human capital accumulation and the public beliefs and attitudes in the action against climate change across the five measures. I also find that individuals with at least primary school education believe that ordinary citizens have a primary responsibility to limit pollution (column (6)) and that in the pursuit of protecting the environment, highly educated citizens believe that the government should impose more and stricter regulations in the extraction of natural resources (column (8)).

Together, the findings in Table 3.3 and Table 3.4, although not evidence of a causal relationship, are in line with recent literature at the intersection of human capital development and adaptation to climate change. For instance, in a global survey, Fagan and Huang (2019) found that people with more education are more likely to perceive climate change as a major threat. Most recently, Angrist et al. (2024) find causal evidence that more years of formal education lead to a substantial increase in pro-climate beliefs, behaviors, and policy preferences in Europe.

3.4.3 The Effects of Education on On-farm Adaptation

In this section, I present and discuss the main results on the impacts of human capital accumulation on on-farm adaptation to climate change that I estimate using the IV strategy.

IV First Stage

I start by reporting the first stage IV results of estimating Equation 3.5 which are presented in Table 3.5.

Table 3.5. First Stage Regression: FPE Impact and Years of Education

	Years of Formal Education	
	(1)	(2)
FPE_{ry}	0.773***	0.781***
	(0.106)	(0.128)
Individual controls	No	Yes
Time trend	No	Yes
Cohort FE	Yes	Yes
Region FE	Yes	Yes
Observations	41,809	41,809
F-Statistic	15.809	33.569

Notes: Controls include gender of the plot manager. All regressions use 1970-1989 birth cohorts from the LSMS-ISA surveys. Robust region-clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

The results show a positive effect of the potential impact of FPE (FPE_{zy}) on individual years of formal education. More specifically, on average, an additional year of school provided by FPE increased an individual's formal education by about 0.8 years. This result is indeed consistent with Chicoine (2019), who, using a relatively large sample size, found that exposure to the program increased years of formal schooling in Ethiopia by 0.134 years. The F-Statistic in both specifications is way above the threshold of 10 — particularly in the preferred specification in column (2) — implying that the instrument is very strong and relevant (Stock and Yogo, 2005).

IV Second Stage

Here, I report and discuss the results of the second stage estimated from Equation 3.6. For completeness, I report both the OLS and the IV (2SLS) results in Table 3.6. The 2SLS estimates reveal substantial and economically meaningful effects of formal education on farmers' adoption of CSA practices demonstrating heterogeneous impacts across different adaptation strategies, with particularly strong effects on soil management and conservation practices.

The 2SLS estimates reveal substantial positive effects of education on CSA adoption in Ethiopia. An additional year of formal education significantly increases the likelihood of adopting several key CSA practices: soil fertility management (4.8 percentage points), crop rotation (12.7 percentage points), improved seeds (2.3 percentage points), irrigation (2.5 percentage points), erosion prevention (10.1 percentage points), and minimum tillage (6.7 percentage points).

Table 3.6. Effects of Education on On-farm Climate Change Adaptation

	Soil Fert.	Mixed Crop	Crop Rot.	Impr. Seed	Use Irrig.	Prevent Eros.	Min Till.
OLS :							
Education	0.008***	-0.001	-0.002	0.002	0.001*	0.000	0.001
	(0.002)	(0.003)	(0.004)	(0.001)	(0.000)	(0.004)	(0.002)
2SLS:							
Education	0.048*	-0.007	0.127***	0.023*	0.025***	0.101***	0.067***
	(0.026)	(0.009)	(0.022)	(0.013)	(0.007)	(0.041)	(0.022)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,809	41,809	41,809	41,809	41,809	41,809	41,809

Notes: Controls include gender the plot manager maker. All regressions use 1970-1989 birth cohorts from the LSMS-ISA surveys sample. Robust region-clustered standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Abbreviations: Fert.=Fertility; Rot.=Rotation; Impr.=Improved; Irrig.=Irrigation; Eros.=Erosion; Min Till.= Minimum tillage.

The strong positive effects across conservation agriculture practices, particularly crop rotation and minimum tillage, demonstrate that well educated farmers are more likely to implement a diverse portfolio of climate-smart practices. The modest but significant impacts on improved seed adoption and irrigation are economically meaningful given the low baseline adoption rates in the sample. These findings have crucial implications for SSA's agricultural sector, where soil erosion and water scarcity are escalating concerns (Lal, 1995; Vlek et al., 2008; Mulinge et al., 2016).

Further analysis summarized in Table A3.1 indicates this effect is primarily driven by increased chemical fertilizer adoption, presenting a complex trade-off between CSA pillars. While chemical fertilizers support the productivity enhancement pillar through improved yields and can aid short-term adaptation through better soil nutrient availability, their relationship with emissions reduction is problematic. Excessive or indiscriminate fertilizer use can contribute to greenhouse gas emissions and soil degradation through increased salinity and acidification, potentially undermining long-term adaptation efforts in SSA where soil degradation already threatens agricultural sustainability (Mulinge et al., 2016).

Together, the results suggest that investments in education could yield substantial returns for agricultural sustainability and climate resilience by enabling farmers to make more sophisticated decisions about farm practices, balancing environmental sustainability with productivity enhancement. This is particularly important in regions where sustainable intensification is increasingly necessary to address climate change challenges.

3.4.4 Robustness and Additional Results

I test the robustness of the main results in two important ways. First, I redefine the outcome variable as the intensity of CSA adoption, which I calculate as an index using the total number of CSA practices adopted by a farmer on a given plot. Second, I recode the outcome variable as a dummy taking the value of 1 if the CSA adoption index is above the sample median. This variable measures the probability of collectively adopting the eight CSA practices. The results reported in Table A3.2 are robust to these alternative measures of CSA adoption. Specifically, an additional schooling year increases the intensity of CSA adoption by 0.24 standard deviations. Relative to sample CSA index mean of 2.4, this implies that the intensity of adoption of CSA increases by 10% due to an additional year of education. In addition, the probability of farmers adopting all CSA practices simultaneously increases by about 10 percentage points.

Furthermore, I extend my analysis beyond the adoption of CSA practices to actual climate resilience outcomes in two important ways. First, FAO (2013) and Jirata et al. (2016) recommend crop loss management as a way to measure the extent of on-farm and off-farm adaptation to changing climate. As a result, I measure on-farm loss management using two proxies: I generate three dummy variables taking the value of 1 if a farmer reports having (i) experienced any crop damage, (ii) if the crop damage is caused by weather risks such as excessive rain, droughts, hail, frost, and floods, and (iii) undertook any prior measure to prevent the damage. To measure off-farm adaptation through post-harvest loss management, I generate a dummy variable that takes the value of 1 if the reported amount of post-harvest losses is zero. Second, I examine education's role on broader household resilience through income (job) diversification and reduced dependence on social safety nets. This analysis is motivated by recent evidence from Musungu et al. (2024), who show that Ethiopian households respond to temporary and persistent drought shocks by reallocating labor to off-farm self-employment activities while maintaining their farming operations. This strategic reallocation of labor suggests that households use income diversification as a key adaptation mechanism. Given that education enhances cognitive abilities, information processing, and opportunity recognition, I hypothesize that more educated farmers are better positioned to identify and capitalize on income diversification opportunities. Furthermore, if education indeed improves overall climate resilience through improved agricultural practices and income diversification, we would expect educated farmers to exhibit reduced dependence on government safety net programs, specifically Ethiopia's Productive Safety Net Program (PSNP). The results from these additional analyses are summarized in Table 3.7 and Table 3.8.

Consistent with my theoretical predictions, I find compelling evidence that the impact of education extends beyond the on-farm adoption of CSA practices to actual climate resilience outcomes. The IV estimates in Table 3.7 reveal that while an additional year of education does not significantly increase the probability of experiencing either general crop damage or weather-related crop damage, it substantially enhances farmers' ability to prevent such damage. Specifically, an additional year of education increases the probability of implementing damage prevention measures by 11 percentage points (significant at the 1% level). This suggests that educated farmers are not necessarily less exposed to climate-related risks but are better equipped to anticipate and mitigate potential crop losses.

Table 3.7. Effects of Education on On-farm Crop Losses

	General crop damage		Weather crop damage		Prevent crop damage	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Education	0.002***	0.004	0.001	0.014	0.001	0.109***
	(0.000)	(0.058)	(0.004)	(0.020)	(0.002)	(0.026)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,809	41,809	18,790	18,790	41,809	41,809

Notes: Controls include gender of the plot manager. All regressions use 1970-1989 birth cohort from the LSMS-ISA surveys sample. Robust region-clustered standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Furthermore, education's role in building adaptation extends beyond on-farm adaptation to building actual resilience as summarized in Table 3.8. First, I find that an additional year of formal education reduces the probability of experiencing post-harvest losses by 2.9 percentage points (significant at 5% level), indicating that educated farmers are better positioned to manage agricultural output even after harvest. Second, using a modified standardized Simpson income diversification index (Simpson, 1949)[6] that uses time allocation across different job categories, I find that an additional year of education increases job diversification by 0.04 standard deviations. Given the sample mean job diversification index of 0.10, this effect represents a meaningful increase in households' diversification behavior, suggesting that human capital accumulation substantially enhances their capacity to engage in multiple economic activities. Third, consistent with the hypothesis about reduced vulnerability, I find that an additional year of education decreases the likelihood of participation in PSNP by 1.2 percentage points. This effect is particularly meaningful given that only 4% of the sample participates in PSNP, suggesting that education reduces dependence on safety net programs by approximately 32.5% relative to the sample mean.

Together, these results provide important insights on climate resilience in SSA. First, they suggest that education's role in building climate resilience extends well beyond on-farm adaptation, enabling households to construct more robust and diverse income portfolios. The substantial increase in job diversification indicates that educated farmers are better equipped to navigate the complex transition toward mixed

[6]The Simpson Income Diversification (SID) index is calculated as SID $= 1 - \sum_{i=1}^{n} P_i^2$, where P_i represents the proportion of income from the i-th source. However, given that respondents mostly misreport their incomes thus leading to zero income values in our context, I modify this index by using the number of hours an individual allocates to each job category in on-farm wage employment, non-farm wage employment, off-farm self-employment, working on family/own farm and temporary jobs.

Table 3.8. Effects of Education on Climate Resilience

	Post-harvest losses		Depend PSNP		Job diversification	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Education	-0.002	-0.029**	-0.002***	-0.012***	0.029***	0.041***
	(0.001)	(0.013)	(0.001)	(0.004)	(0.002)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,569	20,569	53,747	53,747	53,747	53,747

Notes: Controls include gender of the plot manager. Robust region-clustered standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

livelihood strategies, which is increasingly crucial for climate adaptation in rural areas. Second, reduced reliance on safety net programs suggests that education improves households' self-sufficiency and reduces their vulnerability to climate shocks. This has significant fiscal implications, as investments in education could potentially reduce future demands on government social protection systems. Furthermore, the combination of increased income diversification and reduced dependency on the safety net indicates that education facilitates the transition to more sustainable and autonomous adaptation strategies. This highlights the importance of incorporating educational investments into comprehensive climate resilience policies, as education appears to catalyze both immediate adaptive capacity through improved farming practices and longer-term resilience through enhanced livelihood diversification.

3.5 Conclusion

This study examines the relationship between formal education and adaptation to climate change in Ethiopia, focusing on both beliefs about climate change and actual adaptation strategies among farmers. By combining various individual-level data sources, I provide comprehensive evidence on how human capital accumulation through education influences climate adaptation and resilience through multiple channels.

Consistent with the emerging literature, I first show that formal schooling is positively associated with beliefs about climate change and its economic threats. The positive association between higher education attainment and climate beliefs and attitudes not only influences public support for environmental policies but also has significant implications for individual behaviors, particularly in the adoption of on-farm adaptation strategies and building resilience to climate change.

Second, I provide causal evidence for the significant role of education in increasing the adoption of CSA practices and technologies among farmers. Substantial increases in adoption probabilities across various CSA practices, ranging from improved seed use to conservation agriculture and sustainable cropping methods, imply that human capital accumulation equips farmers with the knowledge, skills and perhaps the risk tolerance necessary to implement these crucial adaptive strategies. However, it is important to note that while education also promotes productivity-enhancing agricultural practices such as the use of chemical fertilizers, these practices may not necessarily align with the three pillars of CSA, particularly the environmental sustainability and emissions reduction objectives.

The study further demonstrates that the role of education extends beyond the mere adoption of CSA practices to building actual resilience. Through enhanced risk management capabilities, farmers with more education are better able to prevent crop damage and reduce post-harvest losses throughout the agricultural value chain. Moreover, education enables significant livelihood diversification, with more educated farmers showing greater capacity to engage in off-farm economic activities while maintaining their farm operations. This is evidenced by increased job diversification and reduced reliance on safety net programs, suggesting enhanced household self-sufficiency and reduced vulnerability to climate shocks.

The comprehensive nature of these findings underscores the role of human capital as a fundamental cornerstone in building climate resilience in agricultural systems within SSA and beyond. The impacts of education manifest through multiple complementary channels: improving farmers' capacity to implement climate-smart practices, improving risk management throughout the agricultural value chain, and enabling diversification into off-farm jobs. This multifaceted approach to adaptation is particularly crucial in SSA, where underdeveloped agricultural insurance markets require strong alternative risk mitigation strategies.

These results have profound implications for policy design in low-income countries grappling with the dual challenges of climate change adaptation and economic development. While the widespread implementation of FPE programs in SSA emerges as a powerful indirect tool to improve agricultural resilience, our findings suggest the need for a more nuanced approach to agricultural education. Educational initiatives should be complemented with specific training in optimal input management and integrated soil fertility management approaches that emphasize both productivity goals and environmental sustainability objectives. This could include a greater emphasis on integrated management practices that combine the judicious use of chemical inputs with organic alternatives and other sustainable agricultural practices.

By accelerating human capital accumulation while simultaneously promoting environmentally sustainable practices, educational programs could catalyze a more comprehensive shift toward truly climate-smart agriculture, potentially transforming the agricultural landscape of SSA over the coming decades. However, maximizing these benefits requires careful consideration of the time lag between human capital investments and their manifestation in sustainable and resilient agricultural practices. Policymakers should ensure that educational investments are complemented by policies that enhance access to and use of appropriate agricultural technologies and availability of off-farm opportunities. The magnitude of effects reported in this study underscores the substantial returns to such educational investments, suggesting that human capital accumulation, when properly oriented toward sustainability objectives, could be a key pathway for significantly building climate resilience in SSA's agricultural sector while simultaneously reducing future demands on government social protection systems.

Conclusion

This dissertation examines critical dimensions of climate change impacts and adaptation in Africa's agricultural sector through three interconnected empirical essays. Together, these studies provide important insights into how rural households and farming communities respond and adapt to climate shocks, how rising temperatures affect resource allocation efficiency, and how human capital development shapes climate change beliefs and adaptation behavior. The findings have significant implications for policy design aimed at enhancing climate resilience in African agriculture.

The first essay investigates how rural households in Ethiopia adapt to drought shocks through sectoral labor reallocation. Using panel data and exploiting spatio-temporal variations in drought exposure, the study finds that households reduce on-farm work and increase off-farm self-employment in response to both short-term and persistent droughts. This labor reallocation is driven by drought-related declines in agricultural productivity and helps smooth household consumption and maintain food security. Importantly, households with better access to financial services show stronger ability to reallocate labor to off-farm activities, highlighting how financial inclusion can enhance adaptive capacity.

The second essay extends the impacts of climate change by examining how rising temperatures exacerbate resource misallocation in Tanzania's agricultural sector. Combining detailed plot-level data with satellite weather information, the analysis reveals that increased exposure to temperatures above 30°C is associated with higher aggregate misallocation, particularly driven by land distortions. Furthermore, the study provides novel evidence that secure private property rights to land can help alleviate this temperature-driven misallocation. These results underscore the importance of addressing land market frictions and implementing reforms that strengthen tenure security.

Building on the findings from first two, the third essay investigates how human capital accumulation shapes climate change beliefs, on-farm adaptation and building resilience in Ethiopia. Exploiting the potential impact of free primary education reform, the study reveals multiple channels through which education influences adaptation. First, increased education leads to greater awareness of climate change risks and stronger support for environmental policies. Second, additional years of schooling significantly increase farmers' adoption of CSA practices, though with important nuances. While education promotes productivity-enhancing practices like chemical fertilizer and pesticide use, these may not always align with environmental sustainability goals of CSA. Third, education enhances actual climate resilience through improved risk management, reduced post-harvest losses, and increased income diversification. Notably, educated farmers show greater capacity to prevent crop damage and rely less on safety net programs, suggesting enhanced self-sufficiency.

Several common themes emerge across the three essays. First, the studies demonstrate how various forms of market imperfections — in labor markets, land markets, and human capital — can constrain households' ability to adapt to climate change. Second, they highlight the importance of both private adaptation strategies and public policy interventions in building climate resilience. Third, the essays show

how pre-existing socioeconomic conditions and institutional frameworks mediate the effectiveness of different adaptation responses.

The findings point to several priority areas for policy intervention. First, African governments should strengthen rural non-farm economies and expand access to financial services to help households better cope with climate shocks through income diversification. Second, implementing land reforms that enhance tenure security could improve resource allocation efficiency under climate stress. Third, while continued investment in human capital development is crucial, educational initiatives should be complemented with specific training on optimal input management and sustainable agricultural practices that balance productivity goals with environmental objectives.

Future research could build on this work in several ways. First, examining how different adaptation strategies interact and complement each other could generate insights for designing integrated climate resilience programs. Second, investigating the distributional implications of climate impacts and adaptation responses across different socioeconomic groups would be valuable for targeting interventions. Third, evaluating the cost-effectiveness of various public investments in building adaptive capacity could help optimize resource allocation in climate resilience efforts. Fourth, exploring gender gaps in resource misallocation driven by temperature shocks remains an important avenue for future work.

In conclusion, this dissertation generates important insights about climate change adaptation in African agriculture through rigorous empirical analyses. The findings emphasize that building climate resilience requires coordinated interventions across multiple domains — from market reforms to human capital investments. However, these interventions must carefully balance immediate productivity needs with long-term environmental sustainability goals. As climate change continues to threaten livelihoods in SSA, evidence-based policies informed by this type of research will be crucial for protecting vulnerable farming communities while ensuring environmental sustainability.

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Appendices

A1: Chapter 1 Appendices

Conceptualizing and Estimating Heterogeneous Effects

The effects of weather shocks on household outcomes are reinforced by pre-existing household socioeconomic status (Corno et al., 2020; Ansah et al., 2021; Randell et al., 2022). To this end, we explore variation in treatment effects by considering heterogeneity in household characteristics. To achieve this, we estimate our baseline regression specification conditional on selected socioeconomic characteristics (i.e., subsample regressions).

We consider several household baseline characteristics as candidates for heterogeneity analysis. First, we consider how effects of drought on household labor allocation varies by proximity to market centers. The economic intuition here is that households that are closer to markets will incur lower job switching costs and have more access to non-agricultural jobs than households further away from markets. Similarly, households closer to markets will also have more options for non-farm self-employment (i.e., non-farm businesses). To test this hypothesis, we first construct an indicator for proximity to market centers at baseline by distance in kilometers as follows: we generate a dummy equal to 1 if household's distance to the nearest market center at baseline is less than the sample median distance in kilometers, and 0 otherwise. Second, we probe for potential heterogeneity in effects of droughts driven by baseline household labor endowment. Using household size as a proxy, we generate a labor endowment dummy variable equal to 1 if household size at baseline is greater than the baseline median household size, and 0 otherwise.

Secure property rights minimize transaction costs, enhance efficient resource allocation (Coase, 1960), and are often at the forefront of the sustainable development debate, especially property rights to land (Holland et al., 2022). For farm households, this implies that land tenure security (i.e., landownership) can enhance farm investments and promote efficient resource (labor) allocation between to on-farm and non-farm household activities (Galiani and Schargrodsky, 2011). On the flip side, high on-farm investments may imply high switching costs, which can potentially undermine labor mobility across sectors and space. Considering this, we investigate if there are substantial differences in effects of drought on labor allocation between landowners and non-landowners. To do this, we first generate a dummy equal to 1 if the household-owned land at baseline is greater than the sample median, and 0 otherwise.

Finally, following existing evidence that both formal and non-formal risk management mechanisms can compensate for negative effects of weather shocks on agricultural households (Jayachandran, 2006), we search for evidence on possible heterogeneous effects driven by access to both formal and non-formal risk management products. Specifically, we generate a dummy for financial inclusion if the household used formal financial services and (or) insurance services.

Table A1.1. Balance Test Between Drought and Household Characteristics

Variable	Drought: Year	Drought: Growing Season
Distance to urban	0.002	0.000
	(0.002)	(0.002)
Household size	-0.002	-0.001
	(0.001)	(0.001)
Land size	0.000	0.000
	(0.000)	(0.000)
Financial inclusion	0.007	0.006
	(0.005)	(0.005)
Household head age	0.000	0.000
	(0.000)	(0.000)
Female headed	-0.009	-0.003
	(0.006)	(0.005)
Household head education	-0.007	-0.004
	(0.006)	(0.005)
TLU	-0.002	-0.000
	(0.001)	(0.001)
District fixed effects	Yes	Yes
Observations	3339	3339
R-Squared	0.991	0.984

Notes: The balance test uses the wave 1 sample. Outcome variable for each column is drought in year and growing season, respectively. Regressions control for temperature shocks, average monthly rainfall, and temperature.*** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Effects of Persistent (Cumulative) Droughts

Table A1.2. Effects of Cumulative Droughts on Intensive Labor Allocation Margins

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage Employment				
Drought in the last 2 years	-0.022		0.015	
	(0.055)		(0.168)	
Drought in the last 2 growing seasons		-0.054		-0.019
		(0.082)		(0.220)
R-squared	0.147	0.147	0.176	0.176
Panel B: Self Employment				
Drought in the last 2 years	-1.771***		2.060***	
	(0.445)		(0.382)	
Drought in the last 2 growing seasons		-2.328***		3.407***
		(0.639)		(0.561)
R-squared	0.262	0.263	0.197	0.202
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9968	9968	9968	9968

Notes: The dependent variable is the share of household labor hours spent in a particular employment category expressed as a percentage. Household controls are age, gender, and education of the household head, household size, land size, and use of financial services. Weather controls are temperature shock, average monthly temperature, and average monthly rainfall. Cluster robust standard errors are shown in parentheses. .*** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A1.3. Effects of Cumulative Droughts on Intensive Labor Allocation Margins

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage Employment				
Drought in the last 3 years	-0.082		-0.208	
	(0.062)		(0.151)	
Drought in the last 3 growing seasons		-0.138		-0.254
		(0.096)		(0.181)
R-squared	0.147	0.147	0.176	0.177
Panel B: Self Employment				
Drought in the last 3 years	-1.449***		2.302***	
	(0.449)		(0.448)	
Drought in the last 3 growing seasons		-1.632***		2.877***
		(0.588)		(0.586)
R-squared	0.262	0.262	0.200	0.199
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9968	9968	9968	9968

Notes: The dependent variable is the share of household labor hours spent in a particular employment category expressed as a percentage. Household controls are age, gender, and education of the household head, household size, land size, and use of financial services. Weather controls are temperature shock, average monthly temperature, and average monthly rainfall. Cluster robust standard errors are shown in parentheses. .*** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A1.4. Short Term and Long-Term Effects of Drought on Labor Allocation: Alternative Timing

	Off-farm Wage	On-farm Wage	On-farm Self-employed	Off-farm Self-employed
Drought$_{t-1}$	-0.239	0.126	-3.498***	3.437***
	(0.162)	(0.435)	(1.310)	(0.952)
Drought$_{t-2}$	0.061	-0.176	-1.723**	2.763***
	(0.099)	(0.275)	(0.782)	(0.668)
Drought$_{t-3}$	-0.218	-0.526*	-0.742	1.501*
	(0.135)	(0.289)	(0.867)	(0.793)
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9,968	9,968	9,968	9,968

Notes: outcomes in 2011, 2013, and 2015, respectively. The dependent variable is the share of household labor hours spent in each employment category expressed as a percentage. Household controls are age, gender, and education of the household head, household size, land size, and use of financial services. Weather controls are temperature shock, average monthly temperature, and average monthly rainfall. Cluster robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A1.5. Alternative Timing: Effects of 2010 Drought on Future Labor Allocation

	Farm			Off-farm		
	2011	2013	2015	2011	2013	2015
Panel A: Wage employment						
Drought 2010	0.047	0.320	-0.336	2.059	0.666	0.197
	(0.329)	(0.492)	(0.259)	(1.478)	(1.515)	(1.303)
Panel B: Self-employment						
Drought 2010	-5.488**	-3.641	-0.149	5.211**	-1.523	-1.793
	(2.609)	(2.957)	(2.961)	(2.299)	(1.593)	(1.333)
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes:The Table presents results of the effects of drought measured in 2010 growing season on household labor outcomes in 2011, 2013, and 2015, respectively. The dependent variable is the share of household labor hours spent in each employment category expressed as a percentage. Cluster robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Heterogeneous Effects

Table A1.6. Heterogeneous Effects: Market Proximity

	Farm		Off-farm	
	(1)	(2)	(1)	(2)
Panel A: Wage Employment				
Drought in growing season	-0.102	-0.603**	0.474	-0.551
	(0.114)	(0.291)	(0.800)	(0.631)
Mean of DV	0.513	0.951	4.930	5.673
p-value (1) – (2) = 0	0.110		0.313	
Panel B: Self Employment				
Drought in growing season	-2.794	-4.963***	3.673*	5.371***
	(2.203)	(1.493)	(1.875)	(1.225)
Mean of DV	71.952	69.144	10.738	12.200
p-value (1) – (2) = 0	0.415		0.446	
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	5,039	4,929	5,039	4,929

Notes:The columns labeled (1) and (2) are regressions for the urban distant and urban proximal subsamples, respectively. The dependent variable (DV) is the share of household labor hours spent in each employment category expressed as a percentage. Household controls are age, gender, and education of the head of the household, household size, land size, and use of financial services. Weather controls are temperature shock, average monthly temperature, and average monthly rainfall. Cluster robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A1.7. Heterogeneous Effects: Labor Endowment

	Farm		Off-farm	
	(1)	(2)	(1)	(2)
Panel A: Wage Employment				
Drought in growing season	-0.423**	-0.184	-0.175	0.001
	(0.181)	(0.247)	(0.538)	(0.792)
Mean of DV	0.814	0.517	6.076	3.316
p-value (1) – (2) = 0	0.337		0.834	
Panel B: Self Employment				
Drought in growing season	-4.245***	-3.951**	4.540***	4.701***
	(1.305)	(1.691)	(1.094)	(1.210)
Mean of DV	66.595	80.668	11.551	11.231
p-value (1) – (2) = 0	0.849		0.925	
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	7,157	2,811	7,157	2,811

Notes:The columns labeled (1) and (2) are regressions for the low- and high-labor endowment subsamples, respectively. The dependent variable (DV) is the share of household labor hours spent in a particular employment category expressed as a percentage. Household controls are age, gender, and education of the household head, land size, and use of financial services. Weather controls are temperature shock, average monthly temperature, and average monthly rainfall. Cluster robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A1.8. Heterogeneous Effects: Land Ownership

	Farm		Off-farm	
	(1)	(2)	(1)	(2)
Panel A: Wage Employment				
Drought in growing season	-0.383**	-0.193	0.179	0.024
	(0.185)	(0.187)	(0.600)	(0.492)
Mean of DV	0.857	0.413	6.443	2.427
p-value (1) – (2) = 0	0.344		0.816	
Panel B: Self Employment				
Drought in growing season	-4.366***	-2.632	4.790***	2.611*
	(1.428)	(1.933)	(1.127)	(1.351)
Mean of DV	65.837	82.401	12.783	8.149
p-value (1) – (2) = 0	0.428		0.133	
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	7,124	2,831	7,124	2,831

Notes:The columns labeled (1) and (2) are regressions for the low- and high-land endowment subsamples, respectively. The dependent variable (DV) is the share of household labor hours spent in a particular employment category expressed as a percentage. Household controls are age, gender, and education of the household head, land size, and use of financial services. Weather controls are temperature shock, average monthly temperature, and average monthly rainfall. Cluster robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A1.9. Heterogeneous Effects: Financial Inclusion

	Farm		Off-farm	
	(1)	(2)	(1)	(2)
Panel A: Wage Employment				
Drought in growing season	-0.366**	0.034	-0.089	0.841
	(0.169)	(0.541)	(0.505)	(2.115)
Mean of DV	0.688	1.125	4.791	10.034
p-value (1) – (2) = 0	0.445		0.648	
Panel B: Self Employment				
Drought in growing season	-3.851***	-9.891***	4.507***	9.461***
	(1.314)	(2.726)	(1.045)	(2.444)
Mean of DV	70.542	70.766	11.310	12.879
p-value (1) – (2) = 0	0.031**		0.035**	
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	7,124	2,831	7,124	2,831

Notes:The columns labeled (1) and (2) are regressions for the financially excluded and financially included subsamples, respectively. The dependent variable (DV) is the share of household labor hours spent in a particular employment category expressed as a percentage. Household controls are age, gender, and education of the household head, land size, and use of financial services. Weather controls are temperature shock, average monthly temperature, and average monthly rainfall. Cluster robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Robustness Tests

Table A1.10. Effects of Drought on Household Employment (with Household Fixed Effects)

	Farm		Off-farm	
	(1)	(2)	(1)	(2)
Panel A: Wage Employment				
Drought (year)	-0.005*		0.002	
	(0.003)		(0.006)	
Drought (growing season)		-0.009**		-0.004
		(0.004)		(0.008)
R-squared	0.499	0.499	0.628	0.628
Panel B: Self-employment				
Drought (year)	-0.011		0.051***	
	(0.009)		(0.013)	
Drought (growing season)		-0.007		0.067***
		(0.013)		(0.017)
R-squared	0.580	0.580	0.529	0.529
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9,968	9,968	9,968	9,968

Notes:The dependent variable is a dummy taking a value of 1 if a household has at least one member employed in a given employment category and 0 otherwise. Drought refers to the pre-survey year and pre-survey growing season. Household controls are age, gender, and education of the household head, household size, land size, and use of financial services. Weather controls are temperature shock, average monthly temperature, and average monthly rainfall. Cluster robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A1.11. : Effects of Drought on Household Intensive Labor Allocation Margins (with Household Fixed Effects)

	Farm		Off-farm	
	(1)	(2)	(1)	(2)
Panel A: Wage Employment				
Drought (year)	-0.164*		0.412	
	(0.099)		(0.378)	
Drought (growing season)		-0.287**		0.128
		(0.132)		(0.537)
R-squared	0.555	0.556	0.683	0.683
Panel B: Self-employment				
Drought (year)	-3.014***		3.142***	
	(0.977)		(0.692)	
Drought (growing season)		-3.094**		4.608***
		(1.357)		(0.975)
R-squared	0.598	0.597	0.536	0.538
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9,968	9,968	9,968	9,968

Notes:The dependent variable is the share of household labor hours spent in a particular employment category expressed in percent. Drought refers to the pre-survey year and pre-survey growing season. Household controls are age, gender, and education of the household head, household size, land size, and use of financial services. Weather controls are temperature shock, average monthly temperature, and average monthly rainfall. Cluster robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A1.12. Effects of Drought on Household Consumption (with Household Fixed Effects)

	Food consumption		Non-food consumption	
	(1)	(2)	(1)	(2)
Drought	-0.051***	-0.054***	-0.042***	-0.041***
	(0.011)	(0.012)	(0.015)	(0.015)
OFSE (log)	0.021***	0.018***	0.021***	0.022***
	(0.006)	(0.006)	(0.007)	(0.007)
Drought × OFSE (log)		0.006		-0.002
		(0.004)		(0.005)
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9,968	9,968	9,968	9,968
R-Squared	0.617	0.617	0.663	0.663

Notes:Drought is measured during the growing season. Dependent variables are logarithms of annual food and non-food expenditures per adult equivalent. OFSE stands for off-farm self-employment hours. Household controls are age, gender, and education of the head of the household, household size, land size, and use of financial services. Weather controls are temperature shock, average monthly temperature, and average monthly rainfall. Cluster robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A1.13. Effects of Drought on Food Security (with Household Fixed Effects)

	HDDS (z-score)		HDDS $\geq$ 5 (dummy)		HDDS $\geq$ 7 (dummy)	
	(1)	(2)	(3)	(4)	(5)	(6)
Drought	-0.051***	-0.053***	-0.022**	-0.024***	-0.026***	-0.029***
	(0.015)	(0.015)	(0.009)	(0.009)	(0.008)	(0.008)
OFSE (log)	0.040***	0.039***	0.016***	0.014***	0.011***	0.009**
	(0.007)	(0.008)	(0.004)	(0.005)	(0.004)	(0.004)
Drought $\times$ OFSE (log)		0.003		0.003		0.004
		(0.006)		(0.003)		(0.003)
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,968	9,968	9,968	9,968	9,968	9,968
R-Squared	0.661	0.661	0.558	0.558	0.552	0.552

Notes:Drought is measured during the growing season. HDDS stands for household dietary diversity score. OFSE stands for off-farm self-employment hours. Household controls are age, gender and education of the household head, household size, land size, and use of financial services. Weather controls are temperature shock, average monthly temperature, and average monthly rainfall. Cluster robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A1.14. Conley Robust Standard Errors 15 Km Cutoff: Drought and Intensive Labor Allocation Margins

	Farm		Off-farm	
	(1)	(2)	(1)	(2)
Panel A: Wage Employment				
Drought (year)	-0.151*		0.045	
	(0.084)		(0.329)	
Drought during growing season		-0.345**		-0.074
		(0.160)		(0.515)
R-squared	0.006	0.006	0.066	0.066
Panel B: Self employment				
Drought (year)	-3.294***		2.812***	
	(0.849)		(0.694)	
Drought during growing season		-4.064***		4.492***
		(1.281)		(1.150)
R-squared	0.121	0.120	0.018	0.020
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9,968	9,968	9,968	9,968

Notes:The dependent variable is the share of household labor hours spent in a particular employment category expressed as a percentage. Drought refers to the pre-survey year and the pre-survey growing season. Household controls are age, gender, and education of the household head, household size, land size, and use of financial services. Weather controls are temperature shock, average monthly temperature, and average monthly rainfall. Conley robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A1.15. Conley Robust Standard Errors 25 Km Cutoff: Drought and Intensive Labor Allocation Margin

	Farm		Off-farm	
	(1)	(2)	(1)	(2)
Panel A: Wage Employment				
Drought (year)	-0.151		0.045	
	(0.098)		(0.320)	
Drought (growing season)		-0.345*		-0.074
		(0.176)		(0.504)
R-squared	0.006	0.006	0.066	0.066
Panel B: Self employment				
Drought (year)	-3.294***		2.812***	
	(0.854)		(0.727)	
Drought (growing season)		-4.064***		4.492***
		(1.293)		(1.206)
R-squared	0.121	0.120	0.018	0.020
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9,968	9,968	9,968	9,968

Notes:The dependent variable is the share of household labor hours spent in a particular employment category expressed as a percentage. Drought refers to the pre-survey year and the pre-survey growing season. Household controls are age, gender, and education of the household head, household size, land size, and use of financial services. Weather controls are temperature shock, average monthly temperature, and average monthly rainfall. Conley robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A1.16. Conley Robust Standard Errors 50 Km Cutoff: Drought and Intensive Labor Allocation Margins

	Farm		Off-farm	
	(1)	(2)	(1)	(2)
Panel A: Wage Employment				
Drought (year)	-0.151		0.045	
	(0.099)		(0.308)	
Drought during growing season		-0.345*		-0.074
		(0.179)		(0.474)
R-squared	0.006	0.006	0.066	0.066
Panel B: Self employment				
Drought (year)	-3.294***		2.812***	
	(0.897)		(0.873)	
Drought during growing season		-4.064***		4.492***
		(1.333)		(1.395)
R-squared	0.121	0.120	0.018	0.020
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9,968	9,968	9,968	9,968

Notes:The dependent variable is the share of household labor hours spent in a particular employment category expressed as a percentage. Drought refers to the pre-survey year and the pre-survey growing season. Household controls are age, gender, and education of the household head, household size, land size, and use of financial services. Weather controls are temperature shock, average monthly temperature, and average monthly rainfall. Conley robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A1.17. Alternative Outcome Variable (share of Household Members in Each Job Category)

	Farm		Off-farm	
	(1)	(2)	(1)	(2)
Panel A: Wage Employment				
Drought (year)	-0.002**		-0.001	
	(0.001)		(0.002)	
Drought (growing season)		-0.004**		-0.002
		(0.002)		(0.003)
R-squared	0.125	0.126	0.169	0.169
Panel B: Self employment				
Drought (year)	-0.013*		0.028***	
	(0.007)		(0.006)	
Drought (growing season)		-0.005		0.048***
		(0.010)		(0.010)
R-squared	0.260	0.260	0.340	0.342
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9,968	9,968	9,968	9,968

Notes:The dependent variable is the share of adult household members employed in each employment category. Drought refers to the pre-survey year and the pre-survey growing season. Household controls are age, gender, and education of the household head, household size, land size, and use of financial services. Weather controls are temperature shock, average monthly temperature, and average monthly rainfall. Cluster robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A1.18. Alternative Weather Database: Drought and Extensive Labor Allocation

	Farm		Off-farm	
	(1)	(2)	(1)	(2)
Panel A: Wage Employment				
Drought (year)	-0.004		-0.002	
	(0.003)		(0.005)	
Drought (growing season)		-0.009**		-0.006
		(0.004)		(0.008)
R-squared	0.130	0.130	0.166	0.166
Panel B: Self employment				
Drought (year)	-0.013		0.051***	
	(0.008)		(0.010)	
Drought (growing season)		-0.014		0.071***
		(0.012)		(0.016)
R-squared	0.244	0.243	0.221	0.221
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9,968	9,968	9,968	9,968

Notes:The dependent variable is a dummy taking a value of 1 if a household has at least one member employed in a given employment category and 0 otherwise. Drought refers to the pre-survey year and the pre-survey growing season. Household controls are age, gender, and education of the household head, household size, land size, and use of financial services. Weather controls are temperature shock, average monthly temperature, and average monthly rainfall. Cluster robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A1.19. Alternative Weather Database: Drought and Intensive Labor Allocation

	Farm		Off-farm	
	(1)	(2)	(1)	(2)
Panel A: Wage Employment				
Drought (year)	-0.151		0.045	
	(0.093)		(0.322)	
Drought (growing season)		-0.345**		-0.074
		(0.161)		(0.482)
R-squared	0.148	0.149	0.176	0.176
Panel B: Self employment				
Drought (year)	-3.294***		2.812***	
	(0.834)		(0.610)	
Drought (growing season)		-4.064***		4.492***
		(1.252)		(1.016)
R-squared	0.263	0.262	0.194	0.195
Household controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9,968	9,968	9,968	9,968

Notes:The dependent variable is the share of household labor hours spent in a particular employment category expressed as a percentage. Drought refers to the pre-survey year and the pre-survey growing season. Household controls are age, gender, and education of the household head, household size, land size, and use of financial services. Weather controls are temperature shock, average monthly temperature, and average monthly rainfall. Cluster robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

A2: Chapter 2 Appendices

Recovering Permanent TFP

To recover my benchmark measure of permanent plot-level TFP, I exploit the panel nature of the data to estimate a productivity measure that accounts for spatial and temporal variations in productivity in a two-step process. First I decompose the logarithm of cross-sectional TFP that I residually estimated from Equation 3.1 to extract plot fixed effects as follows:

$$LogTFP_{iht} = \rho_0 + \mu_t^{TFP} + \mu_{ih}^{TFP} + \epsilon_{it}^{TFP} \tag{7}$$

where μ_t^{TFP} is the year fixed effects that absorb other time-varying factors that are common to all decision makers, μ_i^{TFP} is the household-plot fixed effects that are time-invariant and capture persistent productivity differences across households/plot managers, and ϵ_{it}^{TFP} is an error term that absorbs household idiosyncratic shocks in a given year or crop-growing season. Using fixed effects panel data strategy, I estimate Equation 3.4 to extract plot fixed effects μ_i^{TFP} which is inclusive of village fixed effects. I then net out the village fixed effects by regressing μ_i^{TFP} on cluster/village dummies, μ_c as follows:

$$\mu_i^{TFP} = \mu_v^{TFP} + s_i^{TFP} \tag{8}$$

where the predicted error term s_i^{TFP} is a fixed plot component which is the estimate for permanent plot-specific TFP s_i that accounts for time and village fixed effects, which I aggregate to the household-level to get the average measure of household permanent TFP (i.e., household ability). Finally, with this measure of permanent TFP, I redefine my benchmark measure of plot-level real output for each period that abstracts from transitory productivity and land quality from Equation 3.1 as:

$$y_{it} = s_i^{1-\gamma}\left[k_{it}^{\alpha} l_{it}^{1-\alpha}\right]^{\gamma}, \quad \alpha, \gamma \in (0,1) \tag{9}$$

Additional Summary Statistics Tables

Table A2.1. Household Summary Statistics

	N	Mean	SD
Head age	5690	49.061	15.936
Head education	5690	4.856	3.953
Female head	5690	0.244	0.430
Household size	5690	5.559	3.139
Land size (Ha)	5690	1.250	2.416
Crop income (Tsh)	5690	665,016.790	1,080,732.670
Use financial services	5690	0.175	0.380

Table A2.2. Productivity and Misallocation Summary Statistics

	N	Mean	SD
TFP	11747	248966747.372	2.536e+09
TFP(Permanent)	11747	5.511	43.088
TFPR	11747	2.403	34.771
MPL	11747	30.188	533.924
MPK	11747	0.207	5.951

Table A2.3. Association Between Land Quality Index and Land Value

	Log Land Value (Tsh)
Log land quality index	0.094***
	(0.033)
Temperature and rainfall	Yes
Observations	9663
Plot fixed effects	Yes
District fixed effects	Yes
Year fixed effects	Yes
R^2	0.755

Notes: The dependent variable is logarithm of self reported land value in Tsh. The independent variable is logarithm of land quality index. I control for average daily temperature and precipitation. Robust standard errors clustered at the village level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Robustness Tests

Table A2.4. Robustness Test: Temperature and Misallocation

	Log TFPR	Log MPL	Log MPK
Pct.days $\leq 20°$C	-0.003	-0.002	-0.014
	(0.010)	(0.013)	(0.010)
Pct.days $>$20$\leq 25°$C	-0.007	-0.005	-0.020***
	(0.006)	(0.008)	(0.006)
Pct.days $\geq 30°$C	0.022***	0.025***	0.021***
	(0.006)	(0.008)	(0.008)
Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Plot FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	9669	9669	9669
R^2	0.010	0.008	0.014

Notes: These results are from estimating regression specifications that compute HAC standard errors with a distance cutoff of 100KM and a time lag of 10 years. The temperature bins of the share of annual days are relative to the omitted $>$25$<$30°C bin. The controls include rainfall, age, gender and education of the head of the household, and household size. Spatial robust standard errors in parentheses *** p$<$0.01, ** p$<$0.05, * p$<$0.10.

Table A2.5. Robustness Test: Temperature and Misallocation

	Log TFPR	Log MPL	Log MPK
Pct.days $\leq 20°C$	-0.000	0.011	-0.027
	(0.012)	(0.015)	(0.019)
Pct.days $>20\leq 25°C$	-0.008	-0.004	-0.029***
	(0.006)	(0.008)	(0.009)
Pct.days $\geq 30°C$	0.026***	0.027**	0.033***
	(0.008)	(0.012)	(0.013)
Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Plot FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	11615	11615	11615
R^2	0.908	0.877	0.842

Notes: The results are from the robustness test that uses the number of days in the three bins in a year and not the growing season as the outcome variable. The temperature bins of the share of annual days are relative to the omitted $>25<30°C$ bin. The controls include rainfall, age, gender and education of the head of the household, and household size Robust standard errors clustered at the village level in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A2.6. Robustness Test: Temperature and Efficient Allocation

	Log TFPR	Log MPL	Log MPK
Pct.days $\leq 20°$C	0.006***	0.006***	0.007
	(0.001)	(0.002)	(0.008)
Pct.days >20$\leq 25°$C	0.004***	0.003***	0.006
	(0.001)	(0.001)	(0.004)
Pct.days $\geq 30°$C	-0.004**	0.001	-0.019**
	(0.002)	(0.002)	(0.009)
Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Plot FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	11615	11615	11615
R^2	0.980	0.943	0.960

Notes: The results come from robustness check regressions where the outcome variables are the logarithms of the counterfactual measures of TFPR, MPL, and MPK under efficient allocations. The temperature bins of the share of annual days are relative to the omitted >25<30°C bin. The controls include rainfall, age, gender and education of the head of the household, and household size. Robust standard errors clustered at the village level in parentheses *** p<0.01, ** p<0.05, * p<0.10.

Table A2.7. Robustness Test: Temperature and Misallocation

	Log TFPR	Log MPL	Log MPK
Pct.days $>20\leq 25°$C	-0.000	0.011	-0.027
	(0.012)	(0.015)	(0.019)
Pct.days $>25<30°$C	0.003	0.002	0.014*
	(0.004)	(0.005)	(0.007)
Pct.days $\geq 30°$C	0.025***	0.027***	0.035***
	(0.006)	(0.008)	(0.011)
Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Plot FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	11615	11615	11615
R^2	0.908	0.877	0.842

Notes: These results are from regression specifications where I account for multicollinearity in the temperature by omitting the $\leq 20°$C bin. The temperature bins of the share of annual days are therefore relative to the omitted $<20°$C bin. The controls include rainfall, age, gender and education of the head of the household, and household size. Robust standard errors clustered at the village level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A2.8. Land Ownership Right and Land Use Right

Use Right	Fallow	Sale/Collateral	Fallow	Sale/Collateral
Legal Document	0.957***	0.858***		
	(0.010)	(0.016)		
Village Certificate			-0.002	0.015
			(0.011)	(0.012)
Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes
Observations	11654	11654	11654	11654
R^2	0.964	0.928	0.605	0.568

Notes: he controls include average daily temperature and rainfall, age, gender and education of the head of the household, and household size. Robust standard errors clustered at the village level in parentheses. *** p$<$0.01, ** p$<$0.05, * p$<$0.10..

A3: Chapter 3 Appendices

Table A3.1. Education and Soil Fertility Methods

Use of:	Natural fertilizers		Chemical fertilizer	
	OLS	2SLS	OLS	2SLS
Education	0.003**	-0.063***	0.003*	0.055*
	(0.001)	(0.016)	(0.002)	(0.029)
Controls	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	41,809	41,809	41,809	41,809

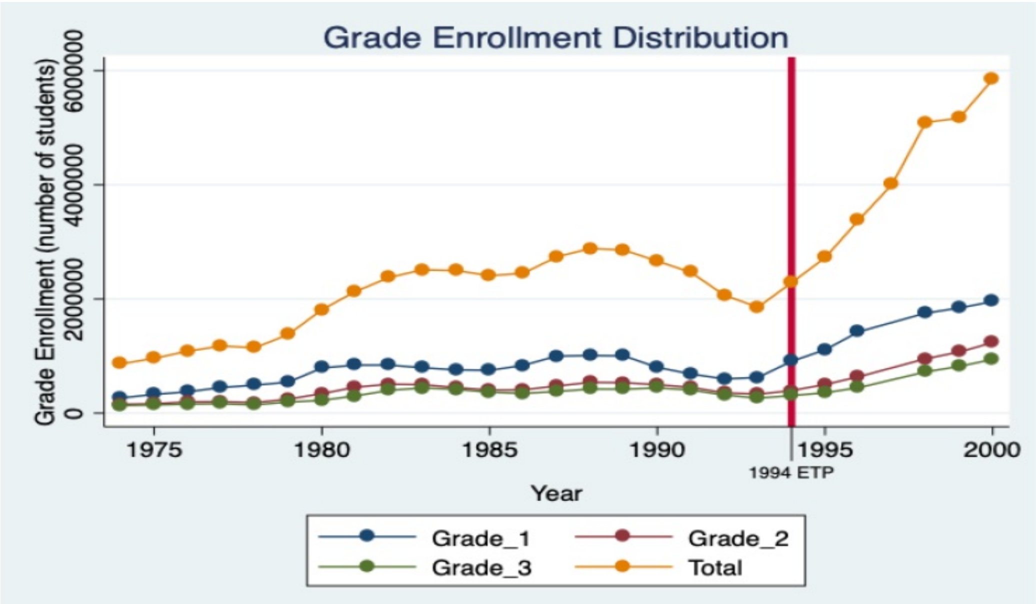
Notes: Controls include gender of the plot decision maker. All regressions use 1970-1989 birth cohort from the LSMS-ISA surveys sample. Robust region-clustered standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$..

Table A3.2. Robustness Test: Alternative Measure of CSA Adopion

	CSA Index		CSA Index > Median	
	OLS	2SLS	OLS	2SLS
Education	0.004	0.242***	0.003	0.098**
	(0.006)	(0.066)	(0.003)	(0.041)
Controls	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	41,809	41,809	41,809	41,809

Notes: Controls include gender of the plot decision maker. All regressions use 1970-1990 birth cohort from the LSMS-ISA surveys sample. Robust region-clustered standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Figure A3.1. Trend in School Enrollment by Grade



Source: UNESCO Institute for Statistics. 1994 ETP refers to the Education and Training Policy implemented in 1994. Increase in grade 1 enrolment was greater than the increase in other grades and before the ETP implementation.