LAND PROPERTY RIGHTS AND RESOURCE MISALLOCATION: EVIDENCE FROM LAND CERTIFICATION PROGRAMMES IN NIGERIA, ETHIOPIA, AND TANZANIA

Mamadou Mouminy Bah[a,b,c]

[a] University of Félix Houphouet-Boigny, Department of Economics, Abidjan, Cote d'Ivoire

[b] Former Research Fellow at the United Nations Economic Commission for Africa, Sub Regional Office for Central Africa, Yaoundé, Cameroon (UNECA-SRO/CA)

[c] Email address: bah.mamadoumouminy@gmail.com

[c] ORCID ID: 0000-0003-0119-2238

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Abstract:

Well-defined and secure property rights over land play an important role in the socio-economic well-being of agricultural households. Using a farm household-level panel dataset, the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA), across three sub-Saharan African countries (Nigeria, Ethiopia, and Tanzania), we examine whether and the extent to which misallocation is associated with property rights, and whether improved land property rights contribute to more efficient factor allocation. Our findings reveal that operated land size and capital are essentially unrelated to farm Total Factor Productivity (TFP), implying substantial frictions in both land and capital markets. These frictions, which result in the misallocation of productive resources, are linked with land institutions that disproportionately constrain the more productive farmers. Moreover, ensuring land security through land certificates leads to the reallocation of land and capital to more efficient farms with positive aggregate effects. Land property rights through the issuance of land certificates facilitate rentals and reduce misallocation, which in turn enhances agricultural productivity. Furthermore, our research indicates that land certificates change the likelihood of households remaining in agriculture, meaning that families who obtained a certificate are more likely to have a household member switching to non-agricultural activities. Our findings suggest that the establishment of decentralised and secure property rights would not only generate large productivity gains but also provide farmers with sufficient incentives to make decisions that enhance the efficiency of resource allocation.

Key words: land property rights, land certification, misallocation, productivity

1. Introduction

It is widely recognised that developing countries have lower total factor productivity (TFP) than developed countries. However, this disparity is more pronounced in the agricultural sector than in non-agricultural sectors (Duarte & Restuccia, 2010; Gollin et al., 2014). Given the high share of agricultural employment in developing countries, it is important to understand these differences in accounting aggregate income differences between developed and developing countries (Gollin et al., 2014; Gollin et al.,2002; Restuccia, 2020; Restuccia et al.,2008). For instance, in poor countries, more than 70% of the labour force is allocated to agriculture, compared to less than 5% in rich countries. At the same time, the labour productivity gap between rich and poor countries is more than 35-fold in agriculture, while it is less than 5-fold in the non-agricultural sectors (Restuccia et al., 2008). The reasons for these productivity gaps are related to resource misallocation across households, which is more widespread in developing countries (Hsieh & Klenow, 2009; Restuccia & Rogerson, 2008, 2013, 2017).

Government assignment of land and the restrictions on its transfer are key factors in explaining resource misallocation (Adamopoulos & Restuccia, 2020). Advocates of these restrictions argue against the efficient use of resources from land markets, favouring common or customary tenure. Despite extensive research efforts, the impact of land property rights through certification on resource allocation, agricultural productivity, and broader implications remains poorly understood.

Many studies have linked resource misallocation to land market institutions including land reforms (Adamopoulos & Restuccia, 2020), property rights reforms (Chari et al., 2021), the role of land titling or certification (Chen, 2017; Gao et al., 2021; Gottlieb & Grobovšek, 2019), and the extent of marketed land across farm households (Adamopoulos et al. 2022; Bolhuis et al., 2021; Chen et al., 2021, 2023) and found that land markets institutions play an important role in the capital reallocation, which further explains the productivity gap across sectors.

In a context where the aim of agricultural policy is to improve productivity, we examine whether and the extent to which misallocation is associated with property rights and whether improved land property rights have led to a more efficient of land and capital. To answer this question, we use household panel data from Nigeria, Ethiopia, and Tanzania. Our findings reveal significant variation in certificated land parcels across space and time in all three countries.

We focus on these three countries for several reasons: Firstly, these countries have low agricultural productivity, a large proportion of employment in agriculture, and smallholder farming or low farm operational scales. For example, In Ethiopia and Tanzania, the agricultural sector accounts for 73.88% and 73.52% of total employment, respectively, compared to 42.48% in Nigeria from 1997 to 2019[1]. The average operational land size in our sample data is 1.22 hectares (Ha), 1.15 Ha, and 2.30 Ha in Nigeria, Ethiopia, and Tanzania respectively. Secondly, property rights over land are not clearly defined institutionally, which can lead to factors of misallocation in the agricultural sector. Our data shows that only a small percentage of farmers in Nigeria (5.4%) and Tanzania (10.89%) have cultivated land with certificates, compared to Ethiopia where land certificates account for 46%. Thirdly, we use a panel dataset of households that provides detailed input and output information on all farms across multiple waves for each country[2]. The data allows us to precisely construct measures of value-added, productivity, and distortions at the farm level.

To analyse how land property rights reduce resource misallocation in these three countries and to measure the extent of misallocation across farmers implied by the land market institutions across countries, we will proceed in three steps. Firstly, following (Deininger & Jin, 2005), we develop a theoretical framework to show that land property rights increase agricultural output (value-added) through land certification. To test this framework empirically, we use representative panel data in Nigeria, Ethiopia, and Tanzania. We estimate the effect of certification on agricultural output using a fixed-effects model and find a positive relationship between land certification and agricultural value added. To investigate the mechanism by which certification plays a role, we estimate the effect of land certification on the land rental market and migration using fixed-effects (FE) and Chamberlain's correlated random effects (CRE) Probit. Our results indicate that the land rental market increases due to the land certification and households obtaining certificates were subsequently more likely to have a migrant member.

In the second step, a heterogeneous firm-industry framework is employed, following (Adamopoulos & Restuccia, 2014, 2020; Lucas, 1978), to measure the gap between marginal products and the overall extent of inefficiency. to measure the gap between marginal products and

[1] World Development Indicators, 2023.

[2] Three waves 2013/2014, 2015/2016 and 2018/2019 for Nigeria, two waves 2013/2014 and 2015/2016 for Ethiopia and three waves 2008/2009, 2010/2011, and 2012/2013 for Tanzania

the overall extent of inefficiency. In this setup, following (Adamopoulos et al., 2022), we assume that weak property rights manifest as "*wedges*" in marginal products, with the characteristic that these wedges are larger for higher productivity farmers who are not able to accumulate additional land and complementary factors, such as capital. To apply this framework, we explore the farm-level panel data to estimate permanent fixed-effect farm productivity and distortions. We find that the aggregate output (productivity) gains from reallocation are large in all three countries. Eliminating misallocation across farmers within space[3] increases agricultural productivity by 122.4%, 53.6% and 100% in Nigeria, Ethiopia, and Tanzania, respectively. Furthermore, by enabling the efficient allocation of factors of production across different regions, the reallocation gains increase to 200%, 120.5%, and 138.2% in Nigeria, Ethiopia, and Tanzania, respectively. According to (Adamopoulos et al. 2022; de Janvry et al. 2015), land policies in these three countries may be responsible for the misallocation of labour across space, which negatively impacts productivity.

Finally, it is argued that property rights could reduce misallocation through land certification. We assess this effect using fixed effects estimation techniques. To conduct this assessment, three specific measures of farm-level misallocation are used: farm-level efficiency gain, farm-level marginal product of land relative to the zone-level average (MPL), and farm-level revenue productivity relative to the zone-level average (TFPR). The farm-level efficiency gain is the ratio of efficient to equilibrium outputs, which is equal one when there is no misallocation. In the absence of misallocation, farm-level MPL and TFPR should be equal to their zone-level average and any deviation from the zone average indicates misallocation. We find that land property rights through certification reduce farm-level misallocation. However, in Ethiopia and Tanzania, the effect is not significant when misallocation is measured by efficiency gains.

Our paper addresses several strands of the literature. Firstly, the relationship between property rights and economic development has been widely debated in the literature. Besley (1995) and Besley and Ghatak (2010) classified two broad categories of the various channels through which property rights affect the efficiency of resource allocation: limiting expropriation and facilitating

[3] Keep in mind that in this paper space or zone refer to state in Nigeria, zone in Ethiopia, and region in Tanzania

market transactions[4]. Generally, well-defined and secured property rights over land incentivise households to engage in productive activities, make investments to maintain or enhance asset value, and trade or lease the asset for other uses (Besley and Ghatak 2010). Feder & Noronha (1987) highlight that insecure tenure reduces investment incentives and productivity levels. This relationship is consistent with the literature showing larger productivity differences in agriculture between developed and developing countries due to frictions that cause inefficient allocation of productive resources (Adamopoulos et al., 2022; Adamopoulos & Restuccia, 2014; Chari et al., 2021; Lagakos & Waugh, 2013).

Second, the paper also examines how land certification, providing more secure property rights leads to land reallocation through land market participation. Many studies have demonstrated the efficiency of land markets in various developing countries, highlighting their effectiveness in transferring land from less productive to more productive farmers (Deininger and Jin 2005, 2008; Do and Iyer 2008; Gao et al., 2021; S. Jin and Jayne 2013; Songqing Jin and Deininger 2009). Additionally, some studies have found that land certification programmes positively affect rental market participation. For example, Deininger et al., (2011) found that land certification programme in Ethiopia increases land tenure security, land-related investment, and rental market participation. Similar results have been reported in China (Chari et al., 2021; Gao et al., 2021; Wang et al., 2018; Zhang et al., 2022). Furthermore, (Adamopoulos & Restuccia, 2020) assessed the effects of land reform on farm size and agricultural productivity in the Philippines, revealing a 17% reduction in agricultural productivity and a 34% decrease in average farm size. Our focus is on land certification reform and its impact through land rental market activity, rather than scale or size across time and space in Nigeria, Ethiopia, and Tanzania.

Several studies examining the impact of land certification programmes on labour reallocation have demonstrated that land tenure security, facilitated by land certificates, significantly influences migration patterns. Securing land property rights for household farmers can reduce the time and resources spent on protecting land. This, in turn, allows them to allocate more time to non-farm sectors (de Janvry et al., 2015; Li et al., 2021; Mullan et al., 2011). de Janvry et al., (2015), found

[4] Limiting expropriation includes two subcategories: strengthening investment incentives by limiting expropriation risks and reducing the need to divert private resources to protect property. Facilitating market transactions has two subcategories: facilitating transactions in assets and credit transactions by improving the collateral capacity of assets.

that households obtaining certificates in Mexico were subsequently 28% more likely to have a migrant member under the land certification programme, consistent with findings by Valsecchi (2014) indicating a 12% increase in migrant members. In contrast, after using micro survey data to estimate the effect of the land titling policy on rural-to-urban migration in China, Li et al., (2021) found no effect of land titling on internal migration in China, attributing this to differences in land property rights structures[5]. In light of these findings, we examine the effect of land certification on labour reallocation (migration) in Nigeria, Ethiopia, and Tanzania.

Third, our paper aligns with existing literature on resource misallocation, particularly in developing countries and with a focus on agricultural productivity (Adamopoulos et al., 2022, 2022; Adamopoulos & Restuccia, 2014; Banerjee & Moll, 2010; Bartelsman et al., 2013; Chen, 2017; Chen et al., 2021, 2023; Hsieh & Klenow, 2009; Oberfield, 2013; Restuccia & Rogerson, 2008, 2017). One key difference is that our focus is on the effect of property rights resource misallocation through land certification across time and space in Nigeria, Ethiopia, and Tanzania.

Finally, another category of existing studies examines whether and how land certification improves agricultural productivity, with some focusing on the relationship between land tenure security and productivity. Banerjee et al.,(2002) found a positive impact of land reforms on agricultural productivity in India, partly due to the increase in investments caused by land tenure security. Recent research, such as Adamopoulos et al.,(2022) and Deininger & Jin(2005) demonstrate that transferring land from less productive to more productive users can resolve the issue of land misallocation, while Chen et al.,(2021, 2023) show that the land rental market reduces misallocation and boosts agricultural productivity. Additionally, studies by Chen (2017) and Gottlieb & Grobovšek (2019) examine the effects of untitled land and communal land tenure on agricultural and aggregate productivity.

Thus, our paper contributes to the literature in two ways: Firstly, it links misallocation to specific policies and institutions, namely land market institutions in Nigeria, Ethiopia, and Tanzania, aligning with earlier studies (Adamopoulos et al.,2022; Chen et al.,2021,2023). Secondly, it contributes to the classical theory of property rights proposed in the literature by exploring the

[5] They explained this difference by the fact that in China, rural land property rights belong to village collectives, while household farmers only have contract and management rights.

broader impact of land property rights on misallocation, including the effects of land certification on land redistribution and labour reallocation. Additionally, we establish a theoretical model Deininger and Jin (2005), to investigate the relationship between land transfer and agricultural output. To investigate the impact of land certification on land transfers, we analyse its effect on transaction costs. Our model demonstrates that land certification reduces transaction costs, leading to an increase in aggregate agricultural output through land reallocation. Finally, we employ various estimation approaches, including Fixed Effect (FE) and Chamberlain's correlated random effects (CRE) Probit.

Though closely related, this study differs from Chen et al., (2021) and Gao et al., (2021) in two ways. Firstly, unlike the former studies that use a geometric mean of farm-level productivity across years or the latter, which estimates permanent farm-level productivity using production functions over two periods, we follow the approach of Adamopoulos et al., (2022) and estimate permanent fixed-effect farm-level productivity, accounting for time factors and other location-specific characteristics. This method is used because the TFP measure may reflect measurement error, transistor output or inputs chock, and unobserved space-specific characteristics, all of which can impact the dispersion of productivity and the implied gains from reallocation. Secondly, while Chen et al., (2021) focus on Ethiopia, and Gao et al. (2021) on China, our study spans three countries, enabling us to conduct a comparative analysis of the effect of property rights not only within a specific country but also across multiple African countries.

The paper is structured as follows: Section 2 provides background information on the current land institutions in Nigeria, Ethiopia, and Tanzania. Section three discusses the data used in more detail, reporting descriptive statistics. Section four presents the analytical framework and the empirical strategy used in the paper. Section 4 presents the main results, and section 6 concludes the paper.

2. Background information on the land institutions in Nigeria, Ethiopia, and Tanzania

Land tenure is a set of regulations governing the ownership and use of land. It is the relationship between the owner and the land and society, as well as the transfer and creation of rights to the land. This section discusses the current state of land institutions in all three countries.

2.1. Land institutions in Nigeria

The Land Use Act of 1978 has been a pivotal law regulating land use and management in Nigeria since its independence in 1960 (Laws of the Federation of Nigeria (LFN), 2004[6], Shittu et al., 2018). Enforced through the Constitution, it establishes land use as the prevailing tenure system, with all land vested in the state. The Act distinguishes urban and rural land[7], granting occupancy rights (or land use rights) through Statutory and Customary Rights of Occupancy[8]. The Certificate of Occupancy serves as the primary land title, issued by the State Governor, and private title registration is permitted on lands gazetted for government use. The Act safeguards customary tenure rights for agricultural land, ensuring compensation and alternative allocation for revoked lands and preserving possession rights for pre-law agricultural land use. Additionally, the Act mandates local authority consent for common-use right transactions.

2.2.Land institutions in Ethiopia

The evolution of land institutions in Ethiopia can be divided into three periods: the imperial period or feudal system (mid-19th century to 1974), the communist regime (1974 to 1991), and the post-communist era. During the first period, Ethiopia's land tenure system, was complex, intertwined with political and class structures, and exhibited interregional variations (Deininger et al., 2008). The southern regions featured a prevalence of absentee landlords and landless tenants, contrasting with the dominance of the Rist system in the north (Rahmato, 1984). The prohibition of land sale or mortgage, coupled with multiple familial claims to the same land based on ancestral use, resulted in widespread land insecurity and disputes. This contributed to political discontent and, ultimately, the fall of the imperial regime in 1975 (Deininger et al., 2008; S. T. Holden & Ghebru, 2016).

In the second period, Ethiopia underwent significant changes as the new communist regime implemented land reform, expropriating all state land, eliminating the wealthy rural landowner elite, and prohibiting land transactions (S. T. Holden et al., 2011; S. T. Holden & Ghebru, 2016). Driven by the ideology of "*Land to the Tiller*," the communist government redistributed land to

[6] https://www.placng.org/lawsofnigeria/view2.php?sn=228

[7] In urban areas, land is under the control and management of the state Governor while all land in non-urban areas is under the appropriated local government

[8] Statutory rights of occupancy are rights to use rural or urban lands granted by the State Governor under the Act, while Customary rights of occupancy are the rights of individuals or communities to lawfully use or occupy land in accordance with customary law, including customary rights of occupancy granted under the Act by local governments

households based on family size or cultivation ability, resulting in a highly egalitarian land distribution (Deininger et al.,2008; S. T. Holden et al., 2009, 2011; S. T. Holden & Ghebru, 2016; S. Holden & Yohannes, 2002). However, these redistributions created land insecurity, viewed as diminishing incentives for investment (Deininger & Jin,2006; S. Holden & Yohannes,2002).

After the overthrow of the communist regime in 1991, the third period in Ethiopia began, with the new government maintaining the state land policy. The 1995 Constitution underscores state ownership of land and grants every household engaged in agriculture inheritable use rights to a piece of land for free. However, the practical realization of this principle, particularly through administrative land redistribution, may conflict with the goal of ensuring tenure security for land users (Deininger et al.,2008). Notably, a reform in the early 2000s introduced land certificates, primarily in the form of land use certificates, to enhance land tenure security. While farmers holding these certificates can rent out their land with restrictions, selling land is prohibited as all land remains state-owned.

2.3.Land institutions in Tanzania

The current land tenure system in Tanzania has developed over three periods: pre-colonial, colonial, and post-colonial (Manysheva 2022). During the colonial era, all land was expropriated by the different tribes, with ownership characteristics based on each tribe's culture, operating under the principle that land belongs to its user [9]. This colonial period can be divide into two phases. Initially, during the German colonial period (1884 - 1917), Crown land, Freeholds for European settlers, Customary land tenure for natives, and Leaseholds were established. Subsequently, under British rule (1918 - 1961), the Land Ordinance of 1923 designated most land as public, introducing Granted rights of occupancy, Deemed occupancy rights, public lands, and freehold tenure.

Since independence, Tanzania's land tenure has been governed by the Land Ordinance of 1923 until 1999. The National Land Policy, implemented through the Land Act 1999 and Village Land Act 1999, provides the legislative framework for land administration and tenure security. The Village Land Act classifies land into communal, occupied, and future categories, empowering

[9] It means that when the household or family is no longer using the land, it is reallocated to another household.

village councils to manage village land, while the Land Act recognises Granted right of occupation and customary right of occupation.

In 1999, a village land certification project began in Mbozi District, certifying 158 out of 175 villages by 2007 under the Village Land Act, resulting in 1,117 Certificates of Customary Right of Occupancy (CCROs) to improve land property rights. Another initiative, the Land Tenure Improvement Project (LTIP), within the Tanzanian Ministry for Lands, Housing and Human Settlements Development, aims to enhance land administration systems, increase land security, and promote land investment. LTIP builds upon previous projects like the Land Tenure Support Project (LTSP) and the Land Tenure Assistance Project (LTAP) to address land insecurity issues through activities such as Increased Tenure Security, Land Information Management, Institutional Strengthening, and Project Management, Monitoring, and Evaluation (M&E)[10].

3. DATA

We use farm household-level panel data from the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA)[11] across Nigeria, Ethiopia, and Tanzania. This dataset, funded by the Bill and Melinda Gates Foundation and implemented by the World Bank's Living Standards Measurement Study (LSMS), comprises four waves of the Nigerian General Household Survey (2010/2011, 2012/13, 2015/16, and 2018/19)[12], two waves of the Ethiopia Socioeconomic Survey (ESS) (2013/14 and 2015/16)[13], and three waves of the Tanzania National Panel Survey (NPS) (2008/09, 2010/11, and 2012/13). These surveys offer comprehensive information on agricultural and household characteristics.

In Nigeria, the original General Household Survey (GHS) - Panel sample[14] was fully integrated with the 2010 GHS Sample. The sample comprised 60 Primary Sampling Units (PSUs) or

[10] For more details about LTIP see : https://www.lands.go.tz/uploads/documents/en/1581735365-RPF%20final%20for%20disclosure.pdf accessed 26 February 2023.

[11] Further information can be found at www.worldbank.org/lsms-isa

[12] Unfortunately wave 2011/2012 does not report land property right, so we exclude this wave in our estimation sample.

[13] Note that there is an additional wave, 2011/12, which unfortunately does not report farm output, so we cannot use this wave in our sample.

[14] An important objective of the GHS-Panel survey is the development of an innovative model for collecting agricultural data in conjunction with household data.

Enumeration Areas (EAs) selected from each of Nigeria's 37 states, totalling 2,220 EAs nationally. Each EA contributed 10 households, resulting in 22,200 households in the GHS sample. From these, 5000 households from 500 EAs were selected for the panel component, with 4,916 households completing interviews in the baseline sample (wave 1-2010/11). The baseline GHS-Panel sample aimed for national and zonal representativeness, with 12 strata comprising urban and rural areas across Nigeria's six geopolitical zones and 37 states.

The objective of the GHS-Panel was to re-interview all households from previous waves and locate those missed in subsequent waves, even if they had moved. Wave 1, 2, and 3 samples comprised the same households, while Wave 4 included both long panel and refresh samples. By Wave 3, the original sample decreased from 4,997 households and 500 EAs to 4,581 households across 486 EAs. Wave 4 consisted of 4,976 households (3,600 new from the refresh sample and approximately 1,500 retained from the long panel sample) across 517 EAs (158 long panel and 359 refresh EAs). Overall attrition since the first wave was 8.3%, with higher rates in certain zones due to security issues, notably 19.5% in the Northeast and 14% in the Southwest[15].

In Ethiopia, the Ethiopian Socioeconomic Survey (ESS) is designed to collect panel data on household and community-level characteristics related to agricultural activities in rural, small town, and urban areas. Conducted in three rounds (ESS1: 2011-2012, ESS2: 2013-2014, ESS3: 2015-2016) nationwide, ESS1 covered rural and small-town areas only, while ESS2 and ESS3 included large town areas, making them nationally representative. ESS2 and ESS3 were utilised in this paper due to ESS1's lack of farm output data. Sampling involved a two-stage probability sample (or sampling strategy), selecting Enumeration Areas (EAs) proportional to population size and 15 households from each EA via simple random sampling approach. The survey covered 10 regions, 69 zones, or 269 districts, interviewing 3,776 households in ESS2 and 4,954 households in ESS3[16].

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[15] For more information, see the survey reports for Nigeria (wave1, wave 2, wave 3 & wave 4) available at:
https://microdata.worldbank.org/index.php/catalog/3557/related-materials (wave 4).
https://microdata.worldbank.org/index.php/catalog/2734/related-materials (wave 3)
https://microdata.worldbank.org/index.php/catalog/1952/related-materials (wave 2)
https://microdata.worldbank.org/index.php/catalog/1002/related-materials (wave 1)

[16]for more information, see the survey reports for Ethiopia (wave 2, wave 3) available at:https://microdata.worldbank.org/index.php/catalog/2247/related-materials (wave 2);
https://microdata.worldbank.org/index.php/catalog/2783/related-materials (wave 3)

In Tanzania, the National Panel Survey (NPS) has regionally representative data for all mainland regions and Zanzibar, covering both rural and urban areas, with a focus on the long rainy season. The original sample in the first wave (2008/09) included 3,265 households clustered in 409 Enumeration Areas (2,063 rural and 1,202 urban households). In subsequent rounds, households from the previous round were grouped into clusters, maintaining continuity. The NPS revisited all interviewed households and tracked relocated adults, resulting in a sample of 3,924 households at the onset of the third round (NPS 2012/2013). By the third round, including households from previous waves and new additions, the sample size increased to 5,015 households. Attrition across the waves remained low, with total household attrition of 4.84%, minimizing the potential for bias within the datasets [17].

This paper focuses on agricultural households, comprising 10,023 households in Nigeria, 5,391 in Ethiopia, and 6,200 in Tanzania (see in Appendix D Table A1). The survey provides detailed information on total household land holdings, physical crop output, and all inputs into production, including labour supply by activity, fertilizer, and farm machinery, for households operating in the agricultural sector. Households are surveyed twice a year, regardless of their participation in agricultural activities. The first round takes place during the planting season, and the second round during the harvest season.

The richness of the data allows us to construct estimates of agricultural output (value added), productivity, capital, labour, land size; quality of land, and land certification at the farm level. For those farmers who have zero capital, but report cultivated land and positive output, we follow (Adamopoulos et al., 2022) and impute for all farmers value equal to the amount of land operated by the household multiplied by 10% of the median of the calculated capital value. Appendix A provides a detailed description of the output (value-added), inputs, land certification measures, and other control variables used in this study.

3.1.Summary statistics

Table 1 reports the distribution of farm sizes across Nigeria, Ethiopia, and Tanzania, indicating significant in average farm sizes. In Nigeria, Ethiopia, and Tanzania, the average farm sizes are 1.224 hectares (Ha), 1.13 Ha, and 2.30 Ha, respectively. Small farms (less than 1 Ha) constitute

[17] https://microdata.worldbank.org/index.php/catalog/2252/related-materials (report wave3)

63.99% and 64.92% of total farms in Nigeria and Ethiopia, while in Tanzania, they account for only 42.77%. Moreover, only 1.63% of Ethiopian farmers in Ethiopia operate more than 5 ha, compared to 3.70% in Nigeria and 9.15% in Tanzania, indicating predominance of smallholdings across all three countries.

Table 1: Land distribution for four farm size groups (ha) in Nigeria, Ethiopia, and Tanzania (% of Farms by Size)

Hectares	Nigeria	Ethiopia	Tanzania
Less than 1 Ha	63.99	64.92	42.77
1-2 Ha	18.68	21.41	24.81
2-5 Ha	13.63	12.04	23.27
More than 5 Ha	3.70	1.63	9.15
Average Farm Size (Ha)	1.224	1.13	2.300

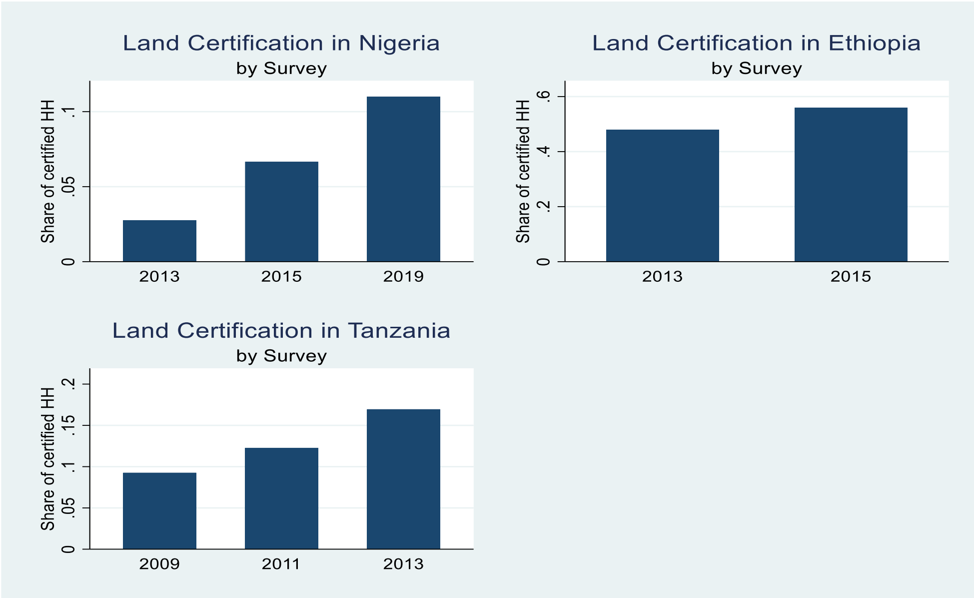
Source: authors' computation based on LSMS-ISA dataset

Tables 2a - 2c provide summary statistics of the main variables categorized by treatment status (certification status)[18]. Statistical analysis reveals significant differences in means between treated (land-certified) and non-treated (land-not certified) households across most variables. In all three countries, treated households exhibit higher average household sizes, more educated heads, greater land ownership, and more parcels compared to non-treated households. Notably, differences in factors such as farm value-added, capital, health status, and factor inputs (land, labour) vary across countries. Additionally, Tables 2a to 2c indicate that non-treatment households in Nigeria and Tanzania are more likely to rent-in land[19], while no significant difference is observed in Ethiopia between the two groups. In Ethiopia and Tanzania, the households that received treatment have older heads than those that did not receive certification, while in Nigeria, the households that did not receive treatment have older heads than those that did. The percentage of certified households increased over time, with Nigeria experiencing growth from approximately 2.75% in 2013/2014 to 11% in 2019/2020, Ethiopia from 47.85% in 2013/2014 to 55.86% in 2015/2016, and Tanzania from 9.3% in 2008/2009 to 17% in 2012/2013 (Figure 1).

[18] Whether the households got the certificates by the time of the survey

[19] Note that we do not have data on rent out land. This may be due to survey design, which is based on arable land or cultivated land, including both owned and rented land; or farmers who rent out land are more likely to be excluded from the sample.

Figure 1: Land certification by survey (year) across countries



Source: author's computation based on LSMS-ISA dataset

Table 2a: Statistical mean of Household characteristics by treatment category in Nigeria.

	Certified	Uncertified	Difference	pvalue
Value-added (Naira)	1.9e+05	2.0e+05	-1.2e+04	0.415
Capital (Naira)	34003.53	17117.74	16885.79	0.281
Labour (days)	365.32	477.11	-111.78	0.000
Land (Ha)	1.58	1.21	0.37	0.000
Owned land	0.94	0.79	0.15	0.000
Rent in (=1)	0.04	0.09	-0.05	0.000
Number of Parcels	2.76	2.38	0.39	0.000
Age of head of HH	49.21	51.81	-2.60	0.000
Head of HH is male	0.93	0.85	0.08	0.000
Head of HH is married (=1)	0.89	0.81	0.09	0.000
Household size	8.22	7.13	1.09	0.000
Head's education: High school (=1)	0.33	0.28	0.06	0.006
Head can read/write (=1)	0.69	0.59	0.11	0.000
Head's health (=1)	0.03	0.04	-0.01	0.150

Source: authors' computation based on LSMS-ISA dataset

Table 2b: Statistical mean of Household characteristics by treatment category in Ethiopia

	Certified	Uncertified	Difference	pvalue
Value added (Birr)	11237.58	11369.41	-131.83	0.863
Capital (Birr)	6196.11	4565.93	1630.17	0.000
Labour (days)	303.40	251.41	51.99	0.012
Land (Ha)	1.38	1.04	0.34	0.000
Owned land	0.91	0.82	0.09	0.000

Rent in (=1)	0.26	0.25	0.01	0.296
Number of Parcels	5.24	4.25	0.99	0.000
Age of head of HH	50.68	43.00	7.68	0.000
Head of HH is male	0.80	0.81	-0.00	0.716
Head of HH is married	0.80	0.82	-0.01	0.226
Household size	6.45	6.07	0.37	0.000
Head's education: High school (=1)	0.00	0.01	-0.01	0.000
Head can read/write (=1)	0.41	0.40	0.01	0.717
Head's health (=1)	0.22	0.20	0.02	0.183

Source: authors' computation based on LSMS-ISA dataset

Table 2c: Statistical mean of Household characteristics by treatment category in Tanzania

	Certified	Uncertified	Difference	pvalue
Value added (ths TZS)	8.5e+05	6.4e+05	2.1e+05	0.0000
Capital (ths TZS)	2.7e+05	2.0e+05	67074.94	0.0842
Labour (Days)	183.43	186.50	-3.07	0.6637
Land size (Ha)	2.32	2.30	0.02	0.8995
Owned land (=1)	0.92	0.81	0.11	0.0000
Rent in (=1)	0.02	0.05	-0.03	0.0000
Number of Parcels	2.49	2.37	0.12	0.0174
Age of head of HH	50.08	48.30	1.78	0.0025
Head of HH is male	0.80	0.77	0.03	0.0529
Household size	6.27	5.66	0.61	0.0000
Head of HH is married (=1)	0.71	0.64	0.07	0.0001
Head can read/write (=1)	0.77	0.69	0.08	0.0000
Head's health (=1)	0.18	0.14	0.04	0.0007

Source: author's computation based on LSMS-ISA dataset

4. Methodology

4.1. Analytical framework

This section outlines a model of agriculture influenced by previous works such as (Adamopoulos & Restuccia, 2014, 2020; Lucas, 1978) adapted to assess the effect of property rights on aggregate output (value added). The model considers a geographic area (Zone level in Ethiopia, State level in Nigeria, and region in Tanzania) populated by heterogeneous household farms indexed by i, each associated with unique locations and TFP levels (farmer's ability or farmer's managerial skills). The agricultural production unit, a farm, necessitates inputs including the farm operator's managerial skills, land, and capital.

Farm production: Households are assumed to produce a homogeneous good and share a common production function, that only differs in terms of their TFP. This production technology exhibits decreasing returns to scale in variable inputs. The output produced by household farm i in zone s and period (wave) t is determined by the Cobb-Douglas function.

$$\tilde{y}_{ijt} = \left(s_{ijt}\nu_{ijt}\right)^{1-\gamma}\left[\left(b_{ijt}l_{ijt}\right)^{\alpha} k_{ijt}^{1-\alpha}\right]^{\gamma};\ \ \alpha,\gamma \in \left(0,1\right) \qquad (1a)$$

Where $\tilde{y}_{ijt}$ is the output of farm (measured as valued added) in household i, zone j at period t, $\left(bl\right)$ represents the quality adjusted land input, where b and l measure land quality and land size, respectively and *k* is the capital stock. γ is the span-of control parameter, which governs the extent of return to scale at farm-level; α captures the land elasticity parameter, and ν is a transitory shock (rain shocks). In our framework, we assume that labour supply across households is the same, although they differ in the number of days worked on the farm. To address this issue, we normalise value-added, capital, and land by total labour days at the farm level to remove the variation in labour. Following Chen et al. (2021 & 2023), we use our data on land quality at the plot or farmer level to eliminate its effect on output. Consequently, our relevant output is defined as output adjusted for land quality and transitory shocks.

$$y_{ijt} = \frac{\tilde{y}_{ijt}}{\nu_{ijt}^{\ 1-\gamma} b_{ijt}^{\ \alpha\gamma}} = s_{ijt}^{\ 1-\gamma}\left(l_{ijt}^{\ \alpha} k_{ijt}^{1-\alpha}\right)^{\gamma};\ \ \alpha,\gamma \in \left(0,1\right) \qquad (1b)$$

Additionally, let $f\left(k,l\right) = y(.)$ and $f(.)$ satisfy the standard assumption:

$$\frac{\partial f\left(.\right)}{\partial k_i} > 0;\ \frac{\partial^2 f\left(.\right)}{\partial k_i \partial k_i} < 0;\ \ \frac{\partial f\left(.\right)}{\partial l_i} > 0;\ \frac{\partial^2 f\left(.\right)}{\partial l_i \partial l_i} < 0$$

$$\frac{\partial^2 f\left(.\right)}{\partial k_i \partial l_i} > 0;\ \left(\frac{\partial^2 f\left(.\right)}{\partial k_i \partial k_i} * \frac{\partial^2 f\left(.\right)}{\partial l_i \partial l_i} - \frac{\partial^2 f\left(.\right)}{\partial k_i \partial l_i}\right) > 0$$

Farmer's Problem:

The planner chooses how to allocate land and capital across farmers in the zone economy to maximize agricultural output subject to resource constraints, taking the rental price of capital (r) and land (q) as given.

If the land rental market is perfect, that is that the rental rate faced by households is determined competitively and that there is no friction or transaction cost. Therefore, household (i) will choose their land and capital by solving the profit maximization problem:

$$\pi\left(s\right) = \max_{\left(k_i, l_i\right)}\left\{\left(s_i\right)^{1-\gamma}\left(l_i^{\alpha} k_i^{1-\alpha}\right)^{\gamma} - rk_i + q\left(\overline{l_i} - l_i\right)\right\} \qquad (2)$$

Where $\overline{l_i}$ and l_i denote the total land endowment and total land operational scale (total agricultural land). r and q are the rental prices of capital and land, respectively. We assume that the agricultural price is normalized to 1.

Using the first order conditions with respect to capital and land, we get:

$$\frac{\partial\pi(s)}{\partial l_i}:\ \alpha\gamma(s_i)^{1-\gamma}\, l_i^{\alpha\gamma-1}k_i^{(1-\alpha)\gamma}=q \tag{3}$$

$$\frac{\partial\pi(s)}{\partial k_i}:\ (1\text{-}\alpha)\gamma(s_i)^{1-\gamma}\, l_i^{\alpha\gamma}k_i^{(1-\alpha)\gamma-1}=r \tag{4}$$

With some algebra, the solutions are characterized by:

$$\begin{cases} l_i^*(s)=\gamma^{\frac{1}{1-\gamma}}\left(\dfrac{\alpha}{q}\right)^{\frac{1-\gamma(1-\alpha)}{1-\gamma}}\left(\dfrac{1-\alpha}{r}\right)^{\frac{\gamma(1-\alpha)}{1-\gamma}} s_i \\ k_i^*(s)=\gamma^{\frac{1}{1-\gamma}}\left(\dfrac{\alpha}{q}\right)^{\frac{\gamma\alpha}{1-\gamma}}\left(\dfrac{1-\alpha}{r}\right)^{\frac{1-\gamma\alpha}{1-\gamma}} s_i \end{cases} \tag{5}$$

Substitute the optimal solution (demand function Eq (5)) back to the definition of profits functions (2), we have:

$$\pi(s_i)=(1-\gamma)(\gamma^{\gamma})^{\frac{1}{1-\gamma}}\left(\frac{\alpha}{q}\right)^{\frac{\alpha\gamma}{1-\gamma}}\left(\frac{1-\alpha}{r}\right)^{\frac{\gamma(1-\alpha)}{1-\gamma}} s_i+q\overline{l_i} \tag{6}$$

Note that the input demand functions and profits are linear in s.

We suppose now there is friction (distortions) in the land. Following Deininger & Jin (2005), this friction is captured by the transaction costs (an implicit distortionary tax on the land rental price of land), faced by farmer i, which includes insecure property rights. Let $T_i=\tau_i(l_i)$ be the transaction cost that farmer i has to pay to operate land size l_i. We assume that $\tau_i(.)$ increases with land size, i.e., $\tau_i'(.)>0$ and household farmer renting in land have to pay an additional tax T_i, in their rent than those renting out land. We assume that T_i, is proportional the area rented and to be equal for those renting in and renting out.

The equilibrium conditions for farmers that do not participate in the rental markets are:

$$\frac{\partial \pi(.)}{\partial k_i}: \ (1\text{-}\alpha)\gamma(s_i)^{1-\gamma} \, l_i^{\alpha\gamma} k_i^{(1-\alpha)\gamma-1} = r \tag{7}$$

$$q - T_i < \frac{\partial \pi(.)}{\partial l_i} = \frac{\partial f(.)}{\partial l_i} = \alpha\gamma(s_i)^{1-\gamma} \, l_i^{\alpha\gamma-1} k_i^{(1-\alpha)\gamma} < q + T_i \tag{8}$$

Equation (8) defines two cut-off points for the farmers' TFP (agricultural ability) denotes as:

$s_l = \left(\frac{q - T_i}{\alpha\gamma l_i^{\alpha\gamma-1} k_i^{(1-\alpha)\gamma}} \right)^{\frac{1}{1-\gamma}}$ and $s_u = \left(\frac{q + T_i}{\alpha\gamma l_i^{\alpha\gamma-1} k_i^{(1-\alpha)\gamma}} \right)^{\frac{1}{1-\gamma}}$, such that households with $s_i \in [s_l; s_u]$ will not engage in land rental markets. households rent out land if $s_i < s_l$, while households rent in land

while $s_i > s_u$

Based above equations, we can derive three propositions (see the proofs in the Appendix B)

Proposition 1: Similarly, in Deininger and Jin's (2005) study, *in an economy without market frictions, the amount of land rented-in increases linearly with agricultural total factor productivity (s).*

Proposition 2: *Similarly, in* Deininger and Jin's (2005) study*, the presence of transaction costs (T) creates a gap between those who rent in and those who rent out land. An increase in transaction costs decreases s_l and increases s_u, thus narrowing the range of producers who remain in autarky. This reduces the number of households participating in rental markets and the amount of land traded in rental markets*.

Proposition 3: *Land certification improves aggregate total factor productivity by reducing the transaction cost in the land rental market.*

4.2.Measuring Efficient Allocation and Farm level productivity (s)

This section describes the methodology used to estimate efficient allocation and farm productivity

4.2.1. Measuring Efficient Allocation

Following Adamopoulos et al. (2022), we derive the efficient allocation that maximises agricultural output given a set of inputs. We show that the efficient allocation involves allocating resources based on relative productivity, with more productive farms receiving more land and capital. We use this efficient allocation and the associated maximum aggregate agricultural output as a benchmark to compare with the actual (distorted) allocations and agricultural output in all three countries (see in Appendix E for more details).

Next, we estimate the farm-specific distortions as implicit input and output wedges or taxes faced by the household farm[20].

$$TFPR_i = \frac{y_i}{l_i^{\alpha} k_i^{1-\alpha}} \equiv \left(\frac{q}{\alpha\gamma}\right)^{\alpha} \left(\frac{r}{(1-\alpha)\gamma}\right)^{1-\alpha} \frac{\left(1+\tau_i^l\right)^{\alpha}\left(1+\tau_i^k\right)^{1-\alpha}}{\left(1-\tau_i^y\right)} \tag{9}$$

TFPR denotes the "Revenue Productivity" as outlined by Hsieh and Klenow (2009). TFPR is proportional to a geometric average of the farm specific land and capital distortions relative to the output distortions. $1+\tau_i^l$ and $1+\tau_i^k$ denotes the land and capital distortions, respectively. $1-\tau_i^y$ is output distortions.

We also derive "Physical Productivity" or TFP for farm i in zone j at period (wave t) from Eq 1b, which is deferent from TFPR

$$TFP_{ijt} = s_{ijt}^{1-\gamma} = \frac{y_{ijt}}{\left[l_{ijt}^{\alpha} k_{ijt}^{1-\alpha}\right]^{\gamma}} \tag{10}$$

Without distortions (i.e. if $\tau_{ijt}^k = \tau_{ijt}^l = 0$), farms with higher physical productivity TFP_{ijt} receive more land and capital and marginal products of each factor TFPR equalise across farms. However, in the presence of distortions, a high (low) farm TFPR is a sign that the farm confronts barriers

[20] We drop time and zone subscripts for convenience

(receives subsidies) that raise (reduce) its marginal products of capital and labour, rendering it smaller (larger) than the optimal size. Therefore, the dispersion of TFPR represents a measure of how severe the distortions are.

Efficiency gain: we measure aggregate agricultural output reallocation gains by comparing efficient output to actual output. Since aggregate factors are held fixed, in this comparison, the output gains represent TFP gains. Therefore, the efficiency gains from eliminating misallocation are given by the ratio of the efficient to the (distorted) observed total output minus one. This efficiency gain represents the measure of misallocation (see in Appendix E for more details).

We also construct corresponding farm-level measures of misallocation to estimate the effect of land certification on misallocation. We also define the farm-level efficiency gain as the ratio of efficient to equilibrium output, $gains_i = \left(y_i^e(s) / y_i^*(s) \right)$, which is equal to one when there is no misallocation. Similarly, we define the farm-level Marginal Product of Land (MPL) and TFPR as:

$$MPL_i = \frac{y_i^*(s)}{l_i^*(s)}; \; TFPR_i = \frac{y_i^*(s)}{k_i^*(s)^{1-\alpha} \, l_i^*(s)^{\alpha}} \tag{11}$$

Absence misallocation, farm-level MPL and TFPR should equal to their zone-level average and any deviation from zone average indicates misallocation.

4.2.2. Measuring Farm Productivity

A key variable in our model and in terms of the impact of property rights on efficiency of production through land certification is farm levels TFP. This TFP is derived residually from the production function (Eq.1) for each time and zone in the data, with adjustments for labour supply variations across households. To address this, we express value-added, capital, and land in per capita (total labour days) terms. We then use this TFP to estimate permanent or farmer-fixed effect level of TFP[21], which controls for productivity variation across the time and location. Specifically, following Adamopoulos et al, (2022), we decompose the logarithm of farm-level TFP:

[21] We prefer using panel data methods with household fixed effects than using proxy variable methods such as (Ackerberg et al., 2015; Levinsohn & Petrin, 2003; Olley & Pakes, 1996).

$$\ln TFP_{ijt} = \lambda_t^{TFP} + \lambda_i^{TFP} + \vartheta_{ijt}^{TFP} \quad (12)$$

Where λ_t^{TFP} is a year fixed effect component that captures time-varying shocks to productivity (e.g., illnesses, weather) that are common across farmers; λ_i^{TFP} is a household farm fixed effect component that does not vary over time; and ϑ_{ijt}^{TFP} is an error term. So, we estimate equation (13) using fixed effect panel data methods to extract the household farm fixed effects λ_i^{TFP}. Note that λ_i^{TFP} is inclusive of zone-level differences. We then remove zone-level differences by regressing the household fixed effect λ_i^{TFP} on zone dummies (λ_z) and extracting the residual.

$$\lambda_i^{TFP} = \lambda_j^{TFP} + e_i^{TFP} \quad (13)$$

Where the predicted error term e_i^{TFP} is our estimate of permanent farm TFP which controls for year and local fixed effects. This procedure provides an estimates of pure farm idiosyncratic fixed effect or permanent component $\hat{e}_i^{TFP}$.

Measuring farm TFP requires values for the parameters α and γ. So, we set these parameters to factor income shares using our microdata. We find in Nigeria, $\gamma = 0.545$, reflecting an income share of labour of 0.455 and $\alpha = 0.80$, implying a land income share of 0.436, and hence a capital income share of 0.11[22]. In Tanzania, we find $\gamma = 0.53$ and $\alpha = 0.77$, while in Ethiopia, we get $\gamma = 0.537$ and $\alpha = 0.72$. These values are in line with findings in developing countries (Adamopoulos et al. 2022; Aragón et al., 2022; Chen et al., 2021, 2023). Adamopoulos et al. (2022), for instance, finds a value for γ that governs the degree of decreasing returns in the production function, of 0.54 from a calibration exercise using data from China. Chen et al., (2023) find a value for γ of 0.42 in Malawi, while Aragón et al., (2022) estimate γ to be 0.708 in Uganda. A lower value of the curvature parameter γ implies a reduced potential of land reallocation relative to larger estimates.

4.3. Empirical Strategy

4.3.1. Land certification and agricultural output (value added)

[22] $\gamma = 1 - labour\ share$, $\alpha\gamma = land\ share$ and $capital\_share = 1 - labour\ sahre - land\ share$

Based on the theoretical model, land certification promotes the free allocation of resource such as land and capital, which improves allocation efficiency and results in higher output. To empirically test the effect of land certification on agricultural output, we estimated the following model:

$$y_{ijt} = \beta certif_{jt} + x'_{ijt}\delta + \lambda_t + \alpha_j + \varepsilon_{ijt} \tag{14}$$

Where y_{ijt} is the agricultural output (value added) of household i, in zone j, and year t α_j represents zone fixed effect, λ_t is a time fixed effect and x_{ijt} is a vector of household level covariates ε_{ijt} is a random error term. We will assess land certification at zone level where the treatment variables $certif_{jt}$ is the treatment dummy variable capturing changes in certificates at zone j. To achieve this, the data is divided into two groups based on changes in certification shares across waves. The treatment group comprises zones where the share of certified land increases between waves, while the control group comprises zones where the share remains the same.

4.3.2. Land certification and land reallocation through rental market

As discussed in the theoretical model, we analyse the effect of land certification on land reallocation via the rental market. To investigate this, we assess how the land certification reform facilitates rentals at the zone level, employing the following empirical specification:

$$Rental_{ijt} = \beta certif_{jt} + x'_{ijt}\delta + \lambda_t + \alpha_j + \varepsilon_{ijt} \tag{15}$$

Where $Rental_{ijt}$ is an indicator of whether household i in zone j engages in renting in in year or waves t. $certif_{jt}$ is the treatment dummy variable capturing changes in certificates at zone j. α_j represents zone fixed effect and the remaining variables are defined as in Equation (14).

4.3.3. Land certification and labour reallocation (migration)

By replacing the dependent variable in Equation (15) with an indicator for whether household i in zone-level j has a migrant worker by wave t, we can examine the effect of land certification on migration. We used the CRE Probit estimator as the estimation method, in addition to the linear fixed effects estimator, as described in Equation (15).

$$Migration_{ijt} = \beta certif_{jt} + x'_{ijt}\delta + \lambda_t + \alpha_j + \varepsilon_{ijt} \qquad (16)$$

Where $Migration_{ijt}$ is an indicator of whether household i in zone j has a migrant worker by year t in year or wave t. $certif_{jt}$ is the treatment dummy variable capturing changes in certificates at zone j. α_j represents zone fixed effect and the remaining variables are defined as in Equation (14).

4.3.4. Effect of certification on land use (Fallowed land)

After demonstrating that land certification influenced factor reallocation (land, labour, or capital), we investigate whether there are efficiency gains from its impact on land use. A decrease in farm labour would typically lead to a reduction in aggregate agricultural output, ceteris paribus. Therefore, if farmers left their land uncultivated after certification, production would decline. We proxy land-use efficiency using the ratio of fallowed land at the zone level, employing the following specification:

$$Fallowed_{ijt} = \beta certif_{jt} + x'_{ijt}\delta + \lambda_t + \alpha_j + \varepsilon_{ijt} \qquad (17)$$

Where $Fallowed_{ijt}$ is and for the share of fallowed land in household i, in zone j and year t, and the remaining variables are defined as in Equation (14).

The empirical Equations (Eq. 15, 16, and 17) are estimated using a linear fixed effect (FE) estimator, which may not be ideal for binary response variables. To address this, we use nonlinear models such as the Probit model. In panel data settings, assuming independence between covariates and unobserved heterogeneity is a strong assumption. Indeed, in our study, the allocation of land certificates may be correlated with unobserved household factors such as attitude and preference. Given such information, estimates from the standard random effect model are only consistent if unobservable factors are not correlated with the error term. To tackle this issue, we adopt the correlated random effects (CRE) Probit estimator, as suggested by (Chamberlain, 1984; Mundlak, 1978; Wooldridge, 2010). This estimator includes average levels of time-varying covariates, which relaxes the independence assumption by modelling the distribution of unobserved effects conditional on exogenous variables. This approach has been used in several studies, including (Adamie 2021; Deininger et al. 2014; Deininger et al., 2011; S. T. Holden et al., 2009)

4.3.5. Land certification and misallocation.

By replacing the dependent variable in Equation (17) with an indicator of misallocation, we examine the effect of land certification on misallocation, using fixed effect specifications follow:

$$Misallocation_{ijt} = \beta certif_{jt} + x'_{ijt}\delta + \lambda_t + \alpha_j + \varepsilon_{ijt} \qquad (18)$$

Where $Misallocation_{ijt}$ is measures of farm-level misallocation. $certif_{jt}$ is the treatment dummy variable capturing changes in certificates at zone j. α_j represents zone fixed effect and the remaining variables are defined as in Equation (14).

We use three specific measures of farm-level misallocation: farm-level efficiency gains; farm-level marginal product of land relative to the zone-level average, and farm-level revenue productivity relative to the zone-level average.

5. Results

In this section, we present the results of the effect of land property right on agricultural output, rental market, migration, and misallocation through land certification.

5.1. Effect of land certification on agricultural output:

Table 3 presents the estimated effect of land certification on household agricultural output (value added) in Nigeria. Column 1 shows that land certification increases agricultural output by 8.2% and this result is robust to alternative estimators and model specifications (Column 2-4). Including household characteristics (Column 2) and replacing zone-fixed effects with household-fixed effects (Columns 3 and 4) do not alter the robustness of the estimated coefficient. In addition, Column 4 includes the interaction terms between each time effect and the result strengthen the positive and significant effect of land certification on household agricultural value-added.

Table 3: Effect of land certification on agricultural Output (Value added) in Nigeria.

	(1)	(2)	(3)	(4)
Land Certified	0.082***	0.065***	0.133***	0.159***
	(0.025)	(0.025)	(0.029)	(0.028)
Observations	7,722	7,705	7,705	7,705
R-squared	0.320	0.327	0.025	0.056

Household Characteristics	No	Yes	Yes	Yes
Time fixed Effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	No	No
Household fixed Effects	No	No	Yes	Yes
Household Characteristics*Time Effect	No	No	No	Yes

Note: Robust Standard errors are given in parentheses. The certified indicator equals one if the zone is certified. Household characteristics include Head of HH is male, Head's education: High school graduate, Head of HH is married age of head of HH and Household size. *** p<0.01, ** p<0.05, * p<0.1

Table 4 presents the effect of land certification on agricultural output in Ethiopia, employing similar methodological approaches as in Table 3. The results indicate that land certification has a positive expected sign, but it is not statistically significant at conventional levels when controlling for zone fixed effect and household characteristics (refer to Column 1 & 2). However, replacing zone fixed effects with household fixed effects (Columns 3 & 4) and incorporating interaction terms between time effects (Column 4) reveal a significant positive effect of land certification on household agricultural output. The results indicate that land certification increases agricultural output by 11.5% and 11.7%, respectively, and are significant at 5%. Therefore, the findings suggest that land certification is still favourable to agricultural output in Ethiopia.

Table 4: Effect of land certification on agricultural Output (Value added) in Ethiopia.

	(1)	(2)	(3)	(4)
Land certified	0.070	0.081	0.115**	0.117**
	(0.052)	(0.052)	(0.055)	(0.055)
Observations	5,391	5,306	5,306	5,306
R-squared	0.182	0.197	0.013	0.020
Household Characteristics	No	Yes	Yes	Yes
Time fixed Effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	No	No
Household fixed Effects	No	No	Yes	Yes
Household Characteristics*Time Effect	No	No	No	Yes

Note: Robust Standard errors are given in parentheses. The certified indicator equals one if the zone is certified. Household characteristics include these variables: Head of HH is male, Head's education: High school graduate (=1), Head of HH is married age of head of HH and Household size. *** p<0.01, ** p<0.05, * p<0.1

Table 5 presents the effect of land certification on output in Tanzania, employing similar methodological approaches as in Tables 3 and 4. Column 1 presents the baseline results, while columns 2-4 control various time trends. The findings indicate a positive and statistically significant effect of land certification on aggregate agricultural output in columns 1, 2, and 4. However, in column 3, replacing zone fixed effects with household fixed effects renders the estimated coefficient non-significant.

Table 5: Effect of land certification on agricultural Output (Value added) in Tanzania.

	(1)	(2)	(3)	(4)
Land certified	0.186*	0.198*	0.058	0.787**
	(0.107)	(0.107)	(0.056)	(0.329)
Observations	6,200	6,200	6,200	6,200
R-squared	0.133	0.141	0.020	0.035
Household Characteristics	No	Yes	Yes	Yes
Time fixed Effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	No	No
Household fixed Effects	No	No	Yes	Yes
Household Characteristics*Time Effect	No	No	No	Yes

Note: Robust Standard errors are given in parentheses. The certified indicator equals one if the zone is certified. Household characteristics include these variables: Head of HH is male, Head of HH is married, age of head of HH and Household size. *** p<0.01, ** p<0.05, * p<0.1

In summary, across all three countries, the findings indicate a positive and significant effect of land certification on household agricultural value added, robust to various model specifications. The coefficients exhibit greater significance and magnitude when accounting for specific time trends more flexibly. These results align with previous studies such as (Deininger et al. 2014; Gao et al., 2021), which also examined the effect of land certification on household productivity in China. Specifically, Deininger et al., (2014) found that households with a certificate are approximately one-third more productive than those without in China, while Gao et al., (2021) showed that land certification increases aggregate output by 23.6% in China.

5.2.Land certification and reallocation: effect of land certification on rentals

Table 6 presents the impact of land certification on rentals in Nigeria. In column 1, controlling for time and zone fixed effects, land certification increases the probability of rental by 2.2%, and the effect is statistically significant. Column 2, including household characteristics, yields similar results. To address concerns about correlated time trends, columns 3-5 introduce various time trend controls, maintaining robust results. Specifically, column 3 replaces zone-fixed effects with household-fixed effects, column 4 allows for zone-specific effects, and column 5 includes interaction terms between time effects and household characteristics. Additionally, in column 6, the Chamberlain’s random effect (CRE) Probit approach confirms a positive and significant effect of land certification on rentals, serving as a robustness check.

Table 6: Effect of land certification on rentals in Nigeria

	(1)	(2)	(3)	(4)	(5)	(6)
Land certified	0.022**	0.020*	0.095**	0.035**	0.021*	0.371***
	(0.011)	(0.011)	(0.039)	(0.017)	(0.011)	(0.060)
Household Characteristics	No	Yes	No	Yes	Yes	Yes
Time fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	No	Yes	Yes	No
Household fixed Effects	No	No	Yes	Yes	Yes	Yes
State*Time Effects	No	No	No	Yes	No	No
Household Characteristics*Time Effect	No	No	No	No	Yes	No
Observations	7,722	7,705	7,722	7,705	7,705	7,705
R-squared	0.096	0.100	0.001	0.127	0.101	
Wald chi2						65.67
sigmau						1.235
rho						0.604
loglikehood						-2626

Note: Standard errors clustered at the zone level are given in parentheses. The certified indicator equals one if the zone is certified. Household characteristics include these variables: Head of HH is male, Head of HH is married, age of head of HH and Household size, Head's education level. *** p<0.01, ** p<0.05, * p<0.1

Tables 7 and 8 present the effects of land certification on rentals in Ethiopia and Tanzania, respectively, using methodologies similar to Table 6. The results indicate a consistent positive association between land certification and land rental share in both countries, robust across various time trend controls and estimation approaches, such as Chamberlain's random effect (CRE) Probit (Column 6). These findings align with theoretical predictions and existing empirical evidence from developing countries (Chen et al., 2021; Cheng et al., 2019; Deininger et al., 2008, 2011; Deininger & Jin, 2005; Gao et al., 2021; S. T. Holden et al., 2011; Qin et al., 2020), suggesting that land certification promotes land reallocation. The impacts are more pronounced in Tanzania compared to Ethiopia and Nigeria.

Table 7: Effect of land certification on rentals in Ethiopia

	(1)	(2)	(3)	(4)	(5)	(6)
Land certified	0.191***	0.188***	0.083***	0.891***	0.186***	1.083***
	(0.036)	(0.035)	(0.008)	(0.019)	(0.035)	(0.135)
Household Characteristics	No	Yes	No	Yes	Yes	Yes
Time fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed Effects	Yes	Yes	No	Yes	Yes	No
Household fixed Effects	No	No	Yes	No	No	Yes
State*Time Effects	No	No	No	Yes	No	No
Household Characteristics*Time Effect	No	No	No	No	Yes	No

Observations	5,391	5,306	5,391	5,306	5,306	5,304
R-squared	0.155	0.157	0.035	0.333	0.162	
Wald chi2						145.3
sigmau						0.372
rho						0.121
loglikehood						-1233

Note: Standard errors clustered at the zone level are given in parentheses. The certified indicator equals one if the zone is certified. Household characteristics include these variables: Head of HH is male, Head of HH is married, age of head of HH and Household size, Head's education level. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Effect of land certification on rentals in Tanzania

	(1)	(2)	(3)	(4)	(5)	(6)
Land certified	0.910***	0.903***	0.596***	0.971***	0.901***	0.164**
	(0.017)	(0.017)	(0.022)	(0.014)	(0.016)	(0.071)
Household Characteristics	No	Yes	No	Yes	Yes	Yes
Time fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	No	Yes	Yes	No
Household fixed Effects	No	No	Yes	No	No	Yes
State*Time Effects	No	No	No	Yes	No	No
Household Characteristics*Time Effect	No	No	No	No	Yes	No
Observations	6,200	6,200	6,200	6,200	6,200	6,200
R-squared	0.728	0.730	0.348	0.737	0.731	
Wald chi2						329.3
sigmau						0.00236
rho						5.59e-06
loglikehood						-3948

Note: Standard errors clustered at the zone level are given in parentheses. The certified indicator equals one if the zone is certified. Household characteristics include these variables: Head of HH is male, Head of HH is married, age of head of HH and Household size, Head's education level. *** p<0.01, ** p<0.05, * p<0.1

5.3.Impact on land certification on household migration decisions

Table 9 presents the results of the effect of land certification on household migration decisions in Nigeria. In column 1, without controlling for household characteristics, the relationship between land certification and migration is positive, economically large (0.461), and statistically significant. When controlling for household characteristics (Columns 2, 4, 5, and 6) and household fixed effects (Column 3), the coefficient remains positive, economically large (0.122 - 0.456). Moreover, the coefficient remains positive and significant, with consistent magnitudes (0.446 - 0.891) when controlling for zone-specific time trends (Column 4) and the interaction between household characteristics and time effects (Column 5). Additionally, employing Chamberlain's random effect (CRE) Probit model (Column 6) yields results consistent with fixed effect (FE) estimates, reinforcing the finding that land certification significantly affects migration in Nigeria.

Table 9: Effect of land certification on migration in Nigeria

	(1)	(2)	(3)	(4)	(5)	(6)
Land certified	0.461***	0.456***	0.122***	0.891***	0.446***	0.488***
	(0.040)	(0.040)	(0.009)	(0.026)	(0.042)	(0.067)
Household Characteristics	No	Yes	No	Yes	Yes	Yes
Time fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	No	Yes	Yes	No
Household fixed Effects	No	No	Yes	No	No	Yes
States*Time Effects	No	No	No	Yes	No	No
Household Characteristics*Time Effect	No	No	No	No	Yes	No
Observations	7,722	7,705	7,722	7,705	7,705	7,705
R-squared	0.567	0.569	0.057	0.666	0.578	
Wald chi2						251.9
sigmau						1.165
rho						0.576
loglikehood						-2154

Note: Standard errors clustered at the zone level are given in parentheses. The certified indicator equals one if the zone is certified. Household characteristics include these variables: Head of HH is male, Head of HH is married, age of head of HH and Household size, Head's education level. *** p<0.01, ** p<0.05, * p<0.1

Tables 10 and 11 present the empirical results of linear fixed effects (FE) and Chamberlain's random effects (CRE) estimations of the effect of land certification on household migration in Ethiopia and Tanzania, respectively, employing methodologies similar to Table 9. The first five columns in Tables 11 and 12 display the linear FE estimates. The study shows that land certification has positive and significant effects on household migration decisions at the conventional level (see Columns 1 to 5). However, in the CRE model (column 6), the relationship between land certification and migration is positive but not statistically significant in Tanzania and Ethiopia compared to Nigeria.

Table 10: Effect of land certification on migration in Ethiopia

	(1)	(2)	(3)	(4)	(5)	(6)
Land certified	0.181***	0.179***	0.078***	0.890***	0.180***	0.051

	(0.036)	(0.036)	(0.012)	(0.021)	(0.036)	(0.113)
Household Characteristics	No	Yes	No	Yes	Yes	Yes
Time fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	No	Yes	Yes	No
Household fixed Effects	No	No	Yes	No	No	Yes
States*Time Effects	No	No	No	Yes	No	No
Household Characteristics*Time Effect	No	No	No	No	Yes	No
Observations	5,371	5,286	5,371	5,286	5,286	5,286
R-squared	0.156	0.158	0.032	0.335	0.163	
Wald chi2						150.1
sigmau						1.262
rho						0.614
loglikehood						-1748

Note: Standard errors clustered at the zone level are given in parentheses. The certified indicator equals one if the zone is certified. Household characteristics include these variables: Head of HH is male, Head of HH is married, age of head of HH and Household size, Head's education level. *** p<0.01, ** p<0.05, * p<0.1

Table 11: Effect of land certification on household migration in Tanzania

	(1)	(2)	(3)	(4)	(5)	(6)
Land certified	0.869***	0.849***	0.477***	0.939***	0.841***	0.515
	(0.015)	(0.017)	(0.019)	(0.016)	(0.018)	(1.081)
Household Characteristics	No	Yes	No	Yes	Yes	Yes
Time fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	No	Yes	Yes	No
Household fixed Effects	No	No	Yes	No	No	Yes
States*Time Effects	No	No	No	Yes	No	No
Household Characteristics*Time Effect	No	No	No	No	Yes	No
Observations	7,530	7,530	7,530	7,530	7,530	7,343
R-squared	0.683	0.691	0.284	0.702	0.695	
Wald chi2						45.43
sigmau						1.563
rho						0.709
loglikehood						-1334

Note: Standard errors clustered at the zone level are given in parentheses. The certified indicator equals one if the zone is certified. Household characteristics include these variables: Head of HH is male, Head of HH is married, age of head of HH and Household size, Head's education level. *** p<0.01, ** p<0.05, * p<0.1

A comparison of the results presented in Tables 9 and 10 & 11 shows that, although the magnitudes of the coefficients change in all three countries, the sign and significance level of the estimates are stable, regardless of the estimation model or estimator applied. In summary, our datasets demonstrate that land certificates result in increased migration rates in Nigeria, Ethiopia, and Tanzania.

Our findings align with studies in China (Gao et al., 2021) and Mexico (de Janvry et al., 2015; Valsecchi, 2014). However, Li et al.,(2021) found no significant effect of land titling or certification on households' internal migration decisions in China, attributing this discrepancy to differences in land ownership rights.

5.4.Impacts of land certification on the share of fallowed land

Tables 12, 13, and 14 present the results regarding the effect of land certification on the share of fallowed land. Column 1 presents the baseline results, while columns 2 - 5 introduce various time trend controls. Across all three countries, land certification is associated with a decrease in the share of fallowed land. However, these effects are statistically insignificant in Tanzania when controlling for household characteristics and including interaction terms between time effects and household-level characteristics (columns 1, 2, and 5 in Table 14). Similarly, in Nigeria, the effects are insignificant when controlling for household characteristics and allowing time effects to be specific by state (column 4 in Table 12). Additionally, an unexpected sign is observed in column 3 of Table 14 when replacing state-fixed effects with household-fixed effects in Tanzania.

Table 12: Effect of land certification on the share of fallowed land in Nigeria

	(1)	(2)	(3)	(4)	(5)	(6)
Land certified	-0.185**	-0.189**	-0.604***	-0.064	-0.185***	-0.813*
	(0.071)	(0.070)	(0.182)	(0.050)	(0.068)	(0.436)
Household Characteristics	No	Yes	No	Yes	Yes	Yes
Time fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	No	Yes	Yes	No
Household fixed Effects	No	No	Yes	No	No	Yes
States*Time Effects	No	No	No	Yes	No	No
Household Characteristics*Time Effect	No	No	No	No	Yes	No
Observations	2,331	2,330	2,331	2,330	2,330	2,330
R-squared	0.370	0.372	0.343	0.409	0.375	
Wald chi2						67.23
sigmau						0.872
rho						0.432
loglikehood						-1125

Note: Standard errors clustered at the zone level are given in parentheses. The certified indicator equals one if the zone is certified. Household characteristics include these variables: Head of HH is male, Head of HH is married, age of head of HH and Household size, Head's education level. *** p<0.01, ** p<0.05, * p<0.1

Table 13: Effect of land certification on the share of fallowed land in Ethiopia

	(1)	(2)	(3)	(4)	(5)	(6)
Land Certified	-0.010**	-0.009*	-0.016**	-0.022***	-0.009*	-0.126**
	(0.005)	(0.005)	(0.008)	(0.006)	(0.005)	(0.059)
Household Characteristics	No	Yes	No	Yes	Yes	Yes
Time fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	No	Yes	Yes	No
Household fixed Effects	No	No	Yes	No	No	Yes
States*Time Effects	No	No	No	Yes	No	No
Household Characteristics*Time Effect	No	No	No	No	Yes	No
Observations	7,219	7,055	7,219	7,055	7,055	7,055
R-squared	0.099	0.102	0.002	0.118	0.102	
Wald chi2						690.6
sigmau						1.259
rho						0.613
loglikehood						-3439

Note: Standard errors clustered at the zone level are given in parentheses. The certified indicator equals one if the zone is certified. Household characteristics include these variables: Head of HH is male, Head of HH is married, age of head of HH and Household size, Head's education level. *** p<0.01, ** p<0.05, * p<0.1

Table 14: Effect of land certification on the share of fallowed land in Tanzania

	(1)	(2)	(3)	(4)	(5)	(6)
Land Certified	-0.085	-0.078	**0.340*** **	-0.106**	-0.079	-0.580***
	(0.052)	(0.053)	**(0.123)**	(0.047)	(0.052)	(0.193)
Observations	2,230	2,228	2,230	2,228	2,228	2,228
R-squared	0.453	0.465	0.158	0.516	0.471	
Household Characteristics	No	Yes	No	Yes	Yes	Yes
Time fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	No	Yes	Yes	No
Household fixed Effects	No	No	Yes	No	No	Yes
States*Time Effects	No	No	No	Yes	No	No
Household Characteristics*Time Effect	No	No	No	No	Yes	No
Number of hhid			2,183			2,181
Observations	2,230	2,228	2,230	2,228	2,228	2,228
R-squared	0.453	0.465	0.158	0.516	0.471	
Wald chi2						66.42
sigmau						0.372

rho	0.121
loglikehood	-647.7

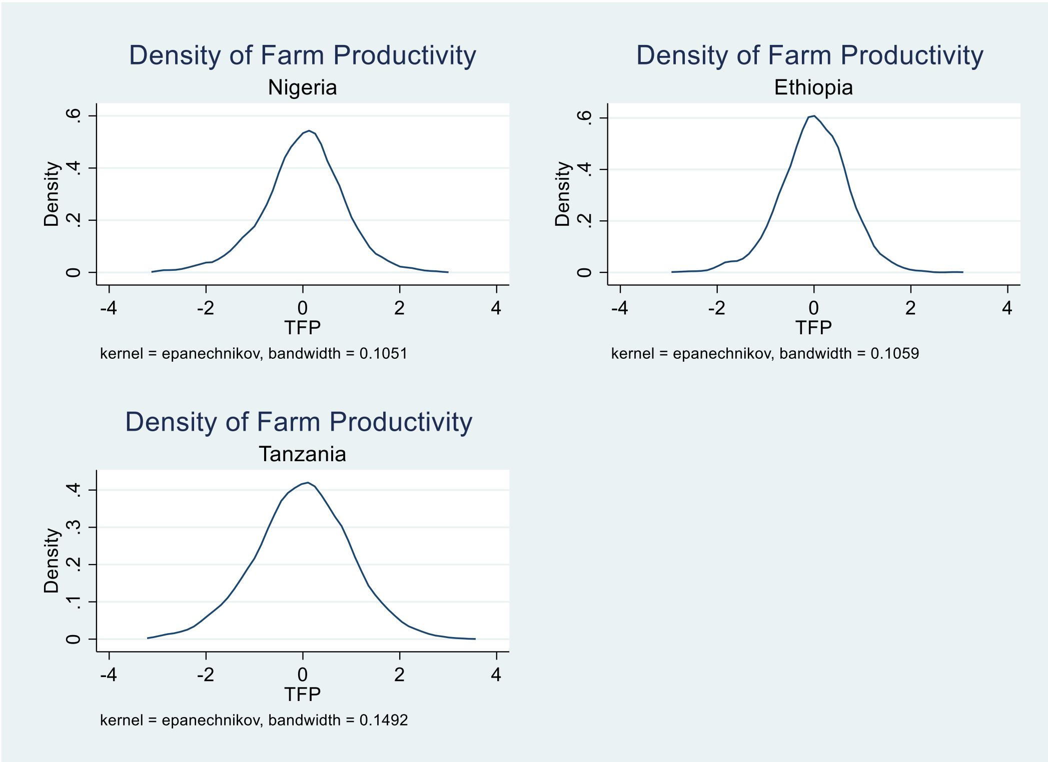
Note: Standard errors clustered at the zone level are given in parentheses. The certified indicator equals one if the zone is certified. Household characteristics include these variables: Head of HH is male, Head of HH is married, age of head of HH and Household size, Head's education level. *** p<0.01, ** p<0.05, * p<0.1

Interestingly, when employing Chamberlain's random effect Probit (CRE) model as a robustness check (column 6 of Tables 12 - 14), our results reveal a consistent negative sign for the coefficient estimates in all three countries, with economically large magnitudes (-0.813 for Nigeria, -0.126 for Ethiopia, and -0.580 for Tanzania), and statistical significance, as expected. In summary, our findings suggest that the share of fallow land decreases with certification, indicating successful resource reallocation, particularly in land use efficiency. These results reaffirm the findings of studies by Gao et al. (2021) in China and de Janvry et al. (2015) in Mexico.

5.5.Distribution of estimated farmer TFP:

After constructing the measure of farm TFP, Figure 3 displays its distribution across all households in Nigeria, Ethiopia, and Tanzania. This figure indicates a notably higher dispersion of farm TFP, measured by the standard deviation, highlighting significant differences in farm productivity across households in all three countries. Specifically, in Nigeria, the dispersion of cross-sectional measures of farm TFP ranges from 1.07 to 1.21 over the period, with an average of 1.148. In Ethiopia, the dispersion ranges from 0.93 to 1.38 over the periods, with an average of 1.159. In Tanzania, the dispersion varies between 1.16 and 1.33 over the periods, with an average of 1.23 (see column 4 of Tables 15a -15c). For further insights into the distribution of farm productivity across years, refer to Annex C.

Figure 3 Density of Farm Productivity s_i (in logs)



In contrast, the baseline fixed effect measure of farm TFP shows a dispersion of 0.857 in Nigeria, 0.676 in Ethiopia, and 0.950 in Tanzania (see column 1 of Table 15a-15c). The 75/25 percentile ratio is 2.98 in Nigeria and 2.36 in Ethiopia, while it is 3.65 in Tanzania. Similarly, the 90/10 percentile ratio is 9.02 in Nigeria, 5.59 in Ethiopia, and 11.36 in Tanzania (see column 1 of Table 16a-16c). The 90/10 percentile ratio and 75/25 percentile ratio remain higher in all three countries when considering the cross-section average (column 4 of Table 15a-15c).

Table 15a: Dispersion of Productivity in Nigeria

	Fixed effects estimates		**Cross-section Average**
	Household Farm	**State**	
Farm TFP			
STD (in log)	0.857	0.9362	1.148
90/10	9.0207	11.14	19.09
75/25	2.984	3.34	4.57
Farm TFPR			
STD (in log)	0.992	1.168	1.339
90/10	12.141	19.75	37.34
75/25	3.528	3.34	6.609
Corr (logTFP, logTFPR)	0.8812	0.8692	0.9276

Table 15b: Dispersion of Productivity in Ethiopia

	Fixed effects estimates		Cross-section Average
	Household Farm	Zones	
Farm TFP			
STD (in log)	0.676	0.806	1.159
90/10	5.581	7.018	28.567
75/25	2.360	2.691	6.428
Farm TFPR			
STD (in log)	0.7863	0.955	1.482
90-10	6.947	9.949	70.435
75-25	2.635	3.257	10.456
Corr (logTFP, logTFPR)	0.8792	0.885	0.9761

Table 15c: Dispersion of Productivity in Tanzania

	Fixed Effects Estimates		Cross-section Average
	Household Farm	Zones	
Farm TFP			
STD (in log)	0.950	1.00	1.230
90/10	11.366	13.632	24.507
75/25	3.649	3.807	5.498
Farm TFPR			
STD (in log)	1.040	1.127	1.363
90/10	14.286	18.459	32.346
75/25	4.177	4.722	6.2121
Corr (logTFP, logTFPR)	0.921	0.9171	0.971

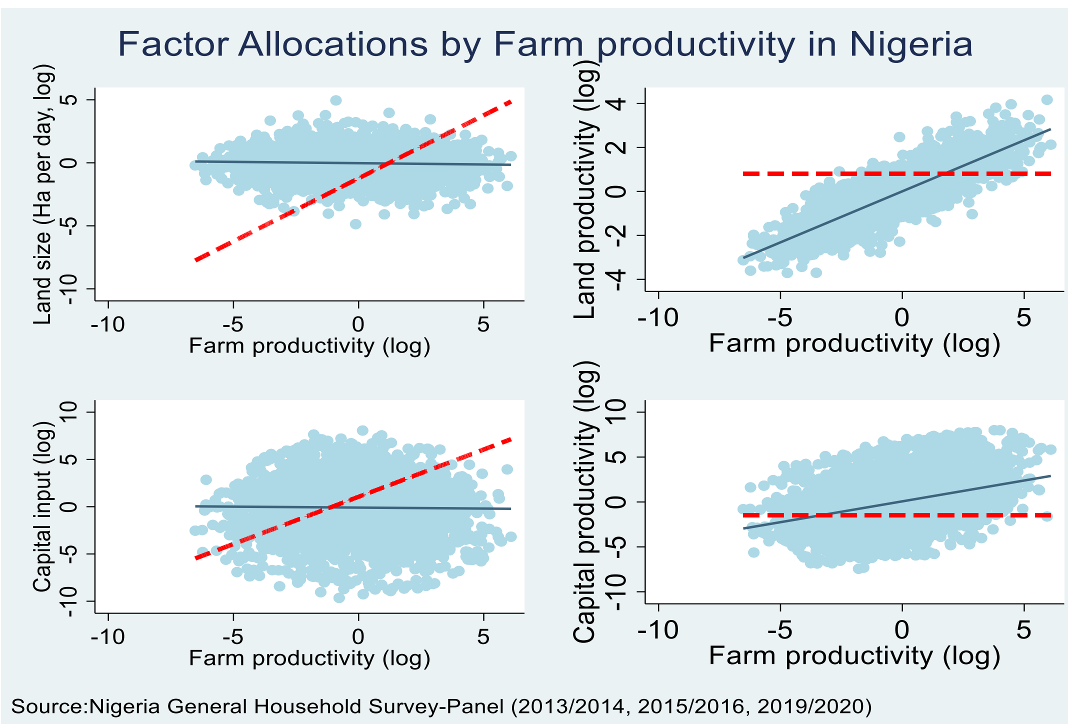
The magnitude of the dispersion in farm productivity is comparable to that found by some authors in Africa. For example, Chen et al. (2023), examining the effect of land misallocation on agricultural productivity in Malawi, reported an average dispersion of farm productivity of 1.19. However, compared to China, where Adamopoulos et al. (2022) found an average dispersion of 0.72 over a 10-year period, the dispersion in farm productivity is higher in these African countries. Furthermore, the estimates reported in Tables 15a-15c (last row) show a notable reduction in the dispersion of productivity and distortions or wedge captured by TFPR when we move from cross-sectional to fixed effects estimates. Additionally, the correlation between farm productivity and farm distortions (TFPR) is significantly higher, ranging from 0.881 in the household fixed effect case to 0.9276 in the cross-section for Nigeria. Similarly, for Ethiopia, the correlation ranges from 0.879 in the household fixed effect case to 0.9761 in the cross-section, and for Tanzania, it ranges from 0.921 in the household fixed effect case to 0.9707 in the cross-section.

5.6.Efficient and actual factors allocations: Distortions and Productivity

If agricultural inputs such as capital and land were distributed equitably among farms through an unconstrained factor market, the resulting allocation would be closer to the efficient allocation. with relatively more productive farmers operating at a larger scale with more land and capital. In this scenario, the correlation between agricultural input usage and TFP would be positive. Factor marginal (and average) product would be uncorrelated with agricultural TFP since, in an efficient allocation, these marginal products are equalised (Adamopoulos et al., 2022).

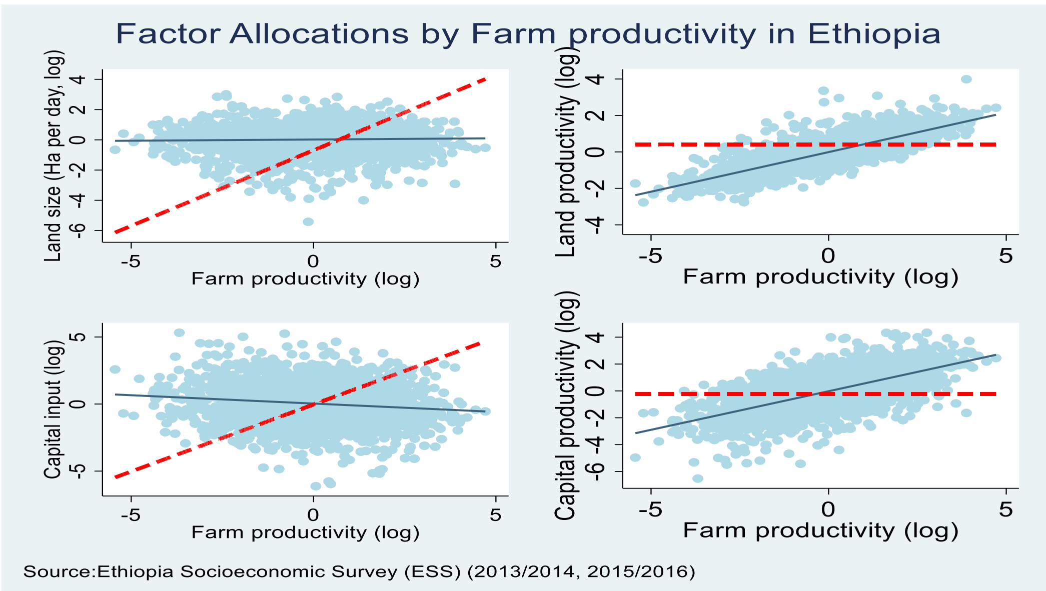
Figure 4a-4c illustrates the allocation of land and capital across farms based on farm-level productivity. The solid line represents the estimated relationship between inputs and farm productivity, while the dashed line represents the efficient allocation associated with each level of farm productivity. In Figure 4a-4c, the top-left (top-right) shows the actual and efficient land size in farms (land productivity) in relation to farm productivity, while the bottom-left (bottom-right) shows the actual and efficient capital in farms (capital productivity) in relation to farm productivity.

Figure 4a: Actual and Efficient Factors Allocations in Nigeria



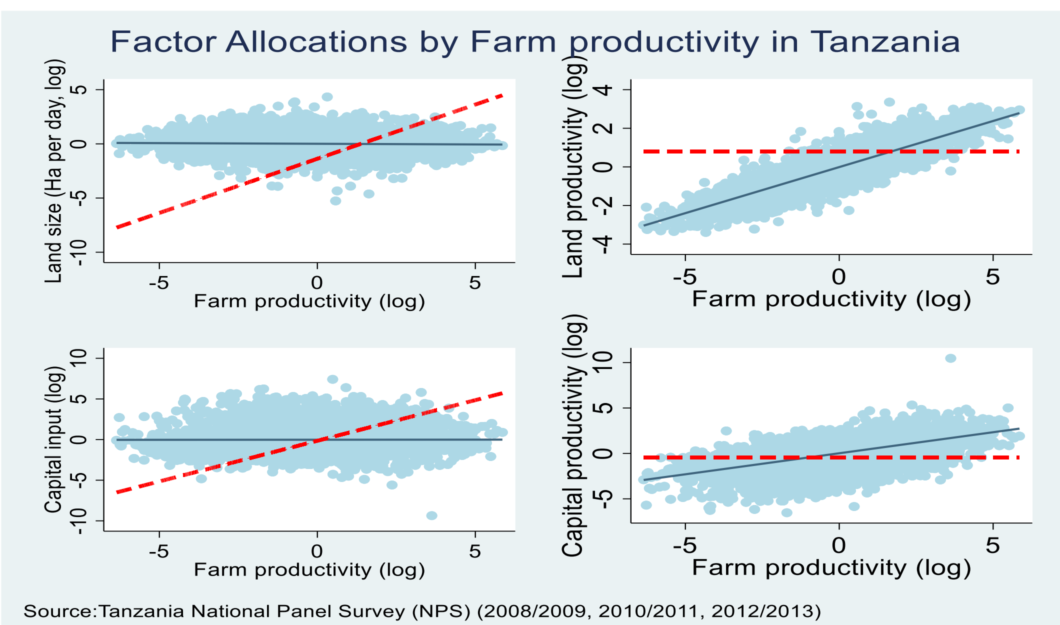
Note: The data on inputs and productivities refer to the permanent household fixed-effect measures removed of time and zone-level factors. Land and capital are measured relative to total labour days supplied to agriculture by the household. Land productivity refers to value added per unit of land and capital productivity refers to value added per unit of capital, both of which are proportional to the marginal products of each factor in our framework. All variables have been logged

Figure 4b: Actual and Efficient Factors Allocations in Ethiopia



Note: The data on inputs and productivities refer to the permanent household fixed-effect measures removed of time and zone-level factors. Land and capital are measured relative to total labour days supplied to agriculture by the household. Land productivity refers to value added per unit of land and capital productivity refers to value added per unit of capital, both of which are proportional to the marginal products of each factor in our framework. All variables have been logged.

Figure 4c: Actual and Efficient Factors Allocations in Tanzania



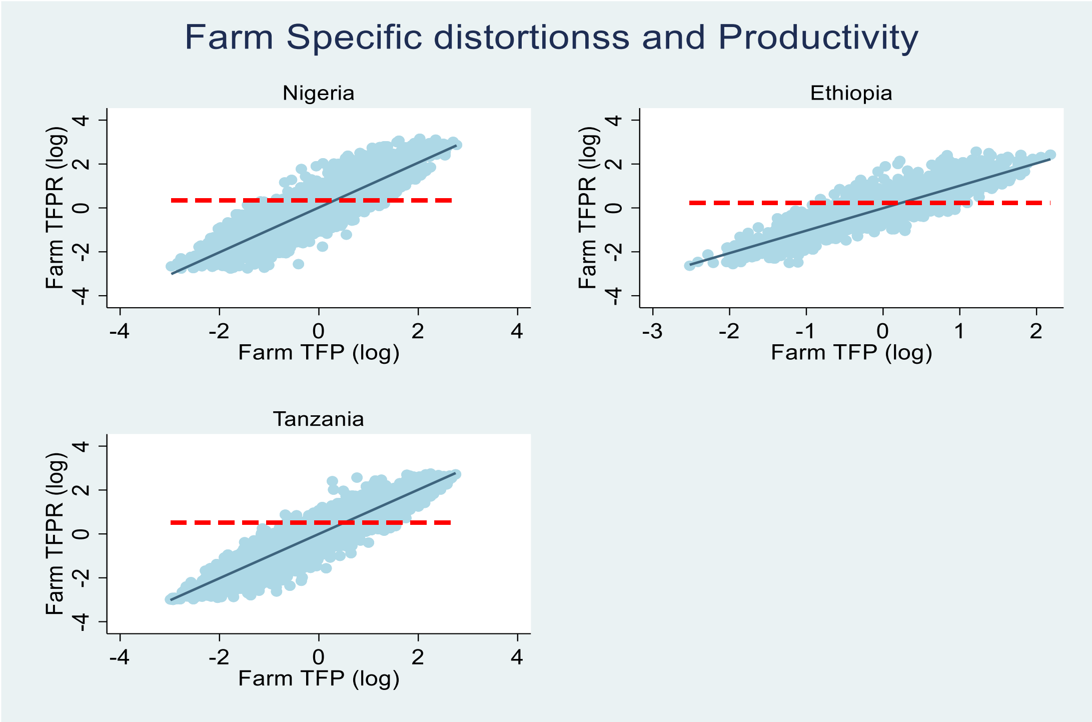
Note: The data on inputs and productivities refer to the permanent household fixed-effect measures removed of time and zone-level factors. Land and capital are measured relative to total labour days supplied to agriculture by the household. Land productivity refers to value added per unit of land and capital productivity refers to value added per unit of capital, both of which are proportional to the marginal products of each factor in our framework. All variables have been logged.

Our results indicate that in all three countries, there is no correlation between land and capital in farms and farm TFP (top-left and bottom-left in Figure 4a to 4c). Specifically, the correlation between land size (capital) and farm productivity is -0.04 (-0.02) in Nigeria, compared to 0.03 (-0.14) in Ethiopia and -0.03 (0.003) in Tanzania. Furthermore, the average productivity of land and capital inputs is positively correlated with farm productivity across farms (top-right and bottom-right in Figure 4a-4c). The correlation between the average productivity of land (capital) and farm production is 0.8541 (0.39) in Nigeria, 0.81 (0.63) in Ethiopia, and 0.8913 (0.59) in Tanzania (see Annexe D for the correlation matrix). The results indicate that these patterns are not consistent with an efficient allocation of resources across farmers in all three countries (dashed lines).

The allocation of land among farmers in Nigeria, Ethiopia, and Tanzania is not correlated with agricultural productivity. This is consistent with our characterization of the land market, where the amount of land on farms is more closely related to inheritance norms and redistribution. It is also possible that the lack of ownership of allocated land, and hence the inability to use the land as collateral, may also contribute to the misallocation of capital. Furthermore, it seems that there is a negative correlation between the use of capital and agricultural productivity in Nigeria and Ethiopia. This weak negative correlation may be due to other frictions in the capital market.

These results are consistent with findings from studies in other developing countries such as Malawi (Chen et al., 2023), China (Adamopoulos et al. 2022), India (Bolhuis et al.,2021)and (Britos et al., 2022). However, in developed countries, some studies have shown a positive relationship between farm size and productivity. For instance, Adamopoulos and Restuccia (2014) found a high positive correlation between farm size and productivity in the US, with a correlation coefficient of approximately 0.90, using the US Census of Agriculture data.

Figure 5: Farm specific distortions and productivity



Our findings strongly indicate the misallocation of land and capital across farmers in Nigeria, Ethiopia, and Tanzania. Within our framework, this misallocation is evident through farm-specific distortions or wedges, measured as disparities in input allocations between actual and efficient allocations. Similar to Adamopoulos et al. (2022), these distortions in both land and capital markets are captured by the Revenue of Total Factor Productivity TFPR).

Figure 5 illustrates the farm-specific distortions (TFPR) against farm Total Factor Productivity (TFP) based on our baseline results. These figures reveal a positive correlation between farm distortions (TFPR) and farm productivity (TFP) in all three countries. This suggests that more productive farmers face higher farm-specific distortions, leading them to produce less, while less productive farmers tend to overproduce. Tables 15a-15c (last row) further validate this strong positive correlation between TFPR and TFP.

5.7. TFP gain from eliminating farm-specific distortions (misallocation): Efficiency gains.

This section presents the efficiency gains from factor reallocation by addressing the question: how would be productivity gains in the absence of farm-specific distortions? Equation 16 is used to estimate productivity gains.

Tables 16a-16b present the efficiency gains using our baseline measure of agricultural TFP, estimated as the fixed effect component of a panel regression, without zone effects. The findings indicate that entirely eliminating misallocation across household farms (within the zone) could potentially boost aggregate agricultural output and TFP by 122.4%, 53.6%, and 100% in Nigeria, Ethiopia, and Tanzania, respectively (first row, first column in Tables 16a, 16b and 16b).

Table 16a: Agricultural Output Gain in Nigeria

Eliminating misallocation across household:	Output gains (Y_eff/Y_actual)			
	Total	Across s misallocation	Land distortion	Cross-Section Average
Within zone	1.224	0.5104	0.7682	1.377
Across zone	2.00	0.80	-	2.262

Table16b: Agricultural Output Gain Ethiopia

Eliminating misallocation across households:	Output gains (TFP) gain (Y_eff/Y_actual)			
	Total	Across s misallocation	Land distortions	Cross-Section Average
Within zone	0.536	0.289	0.392	0.887
+Across zone	1.205	0.809	-	2.206

Table16c: Agricultural Output Gain in Tanzania

Eliminating misallocation across households	Output gains (TFP) gain (Y_eff/Y_actual)			
	Total	Across s misallocation	Land distortions	Cross-Section Average
Within zone	1.001	0.528	0.712	1.258
+Across zone	1.382	0.696	-	1.832

Note: in Tables 16a to 16b, output (TFP) gain is expressed as a percentage. The term "Total" refers to the fixed-effects estimates from the panel regression. "Across s misallocation" refers to the reallocation gains achieved by eliminating misallocation across farm households with different productivity. "Land distortion" indicates the efficiency gain resulting from removing the output wedge stemming from land institutions. "Cross-section average" refers to reallocation gains computed for each cross-section, where farm TFP and distortions are computed for each wave in the panel and then averaged across waves.

The results suggest severe misallocation of factor inputs in all three countries, implying substantial aggregate productivity gains. There are two cases of factor misallocation: factor inputs are dispersed among households with similar levels of productivity and factor inputs are misallocated across households with different levels of productivity. This is confirmed by the top and bottom left panels in Figures 4a to 4c. Moreover, a significant portion of the reallocation gains, approximately 51.5%[23], 59.15%[24], and 61.12%[25] in Nigeria, Ethiopia, and Tanzania, respectively, are a result of reallocating resources among farming households with different TFP. These reallocations would increase agricultural output by 51.04%, 28.90% and 52.8% in Nigeria, Ethiopia, and Tanzania, respectively (first row, second column in Tables 16a, 16b, and 16b). Furthermore, for reallocation of inputs across zones, i.e., using household productivity measures without eliminating zone-specific effects but controlling for zone land quality, the reallocation gain would increase to 200%, 120.5%, and 138% in Nigeria, Ethiopia, and Tanzania, respectively (second row, first column in Tables 16a, 16b, and 16c).

When measuring agricultural TFP, it is important to consider time effects, transitory shocks, and other factors. The conventional cross-sectional measures used in the literature may not account for these factors. In Nigeria, the average reallocation gains are 137.7% within zones and 226.2% across zones. In Ethiopia, the gains are 88.7% within zones and 220.6% across zones. In Tanzania, the gains are 125.8% within zones and 183.2% across zones. Cross-sectional estimates may overestimate the gains from reallocating factor inputs.

In summary, our baseline results suggest a significant increase in productivity due to a reduction in misallocation. This is compared to the results obtained when eliminating all wedges in manufacturing in China and India, as reported in Hsieh and Klenow's (2009) study, with increases ranging between 100% to 160%. Similarly, removing farm-specific distortions or misallocation across household farms in China (within villages) resulted in output gains of 24.4%, as reported in Adamopoulos et al.'s (2022) study. However, our findings are in line with Chen et al. (2023), who found that reallocating capital and land efficiently could increase productivity in Malawi by 260 percent

[23] Log (1.51) /log (2.224)
[24] Log (1.289)/log(1.536)
[25] Log (1.528) /log (2.001)

5.8. Effect of land certification on misallocation

It has been demonstrated that land certification facilitates rentals and reduces misallocation, which in turn enhances agricultural productivity. This effect was assessed through fixed-effects estimation, and the results are presented in Table 17. The land certification reform significantly reduces efficiency gain, with estimated coefficients of -0.132, -0.032, and -0.090 in Nigeria, Ethiopia, and Tanzania, respectively (columns 1, 4, and 7 in Table 17 for Nigeria, Ethiopia, and Tanzania, respectively). While in Ethiopia and Tanzania, the coefficients are not significant when misallocation is measured as efficiency gains. Additionally, coefficients associated with land certification using other measures of farm-level misallocation, such as MPL and TFPR, are also negative and significant in all three countries. These results align with Chen et al.'s (2021) findings, which highlight that the coefficients associated with land certification are considerably smaller than those associated with land rental. This is because certification reform does not fully account for the relationship between rentals and misallocation, or in other words, the causal effects of certification reform do not capture the overall impact of the land market on misallocation and productivity. Besides the scarcity of land certificates, other factors or frictions may also impede rentals and allocative efficiency, such as delays in land reallocation after certificate issuance (Chen et al., 2021).

Table 17: Effect of land certification on misallocation

	Nigeria			Ethiopia			Tanzania		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Eff_gain	TFPR	MPL	Eff_gain	TFPR	MPL	Eff_gain	TFPR	MPL
Land certification	-0.132***	-0.113***	-0.117***	-0.032	-0.050**	-0.058**	-0.090	-0.122**	-0.115*
	(0.022)	(0.019)	(0.022)	(0.022)	(0.021)	(0.023)	(0.064)	(0.059)	(0.067)
Observations	7,722	7,722	7,722	4,718	4,718	4,718	6,200	6,200	6,200
R-squared	0.390	0.360	0.322	0.343	0.296	0.199	0.754	0.739	0.716
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zone fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

6. Conclusion

Using a quantitative framework and farm-level panel data for three countries, we examine the effect of a land certification program on factor reallocation and aggregate output in Nigeria, Ethiopia, and Tanzania. First, we find that a reallocation of factors (land and capital) to their efficient uses could increase agricultural TFP across farmers within zones by 122.4%, 53.6% and 100% in Nigeria, Ethiopia, and Tanzania, respectively. This evidence shows that land and capital are severely misallocated among farmers within zones in all three countries. Second, we estimate a permanent measure of farm productivity that controls for variation in productivity across time and space and show that operated land size and capital are unrelated to household-farm TFP, evidence of substantial misallocation in the agricultural sector. Third, we find that ensuring land security for farmers in the form of land certificates leads to the reallocation of factors inputs to more efficient farms, resulting positive aggregate effects. Moreover, we show land certification facilitates rentals, and reduces misallocation, which in turn enhances agricultural productivity. Additionally, obtaining certificates alters the likelihood of households remaining in agriculture, as families with certificates were more likely to have migrant members in the household. Finally, our findings indicate that land certification is associated with a decline in the share of fallowed land.

Our results provide important policy implications and suggest that the implementation of a secure property rights system to facilitate the decentralized allocation of land would not only generate large productivity gains but also create sufficient incentives for households to make choices that improve the efficiency of resource allocation. Therefore, policymakers should consider land tenure security as a priority to ensure the success of sustainable land use programs and promote the development of modern agriculture. Increased productivity and farm size due to better allocation of inputs among farmers can also induce changes in farm management by providing incentives for farmers to use modern inputs and better technology. We leave these important areas of research for the future.

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Appendix

Appendix A: Descriptions of variables

This sections describes the main variables that we used in our study. We use farm household-level panel data from the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) across Nigeria, Ethiopia, and Tanzania. This dataset, funded by the Bill and Melinda Gates Foundation and implemented by the World Bank's Living Standards Measurement Study (LSMS), comprises four waves of the Nigerian General Household Survey (2010/2011, 2012/13, 2015/16, and 2018/19), two waves of the Ethiopia Socioeconomic Survey (ESS) (2013/14 and 2015/16), and three waves of the Tanzania National Panel Survey (NPS) (2008/09, 2010/11, and 2012/13). These surveys offer comprehensive information on agricultural and household characteristics.

Measure of land property rights: Several indicators on land property right are available in the survey. For each plot that the household owns or uses, the following information is available: whether a household has any legal certificate or title for this plot, and -if the answer is - "yes" - what type of legal certificate or title. Using this information for each plot, we compute the measure of land property rights at the household level as a share of total land that satisfies this criterion. Therefore, the measure of land property rights in our paper is certification share or land titling share.

Output (Value added): We utilise the detailed information on farm output by crop in physical terms to construct estimates of gross farm output. Output of each crop is measured by multiplying the physical quantity (in kilogrammes) produced with its common set of prices, which are constructed as the median price among all different sales (or transactions) for each crop. We then aggregate the values of all crop types produced by the farm to obtain the gross output of each farm. Intermediate inputs (fertilizers, herbicides, pesticides, seeds, etc.) are treated in an analogous way. We subtract the value of intermediate inputs from the value of gross output to obtain the estimate of agricultural value added at the farm level.

Besides, we use the annual precipitation which is the total rainfall in millimetres (mm) in the last 12 months and provided in the data to exclude transitory shocks in output from value added. Therefore, we regress the agricultural value added on the annual precipitation and obtain the residual of this regression as the value-added net of transitory shocks. Thus, we use this benchmark measure of ***value added*** at the farm-level when we refer to agricultural output.

Labour inputs: we construct farm labour input as the sum of days from all three types of labour (farmers' family labour, hired labour, and unpaid labour from other households) for all land plots of the farm. While the **land size** (i.e., farm size) is the sum of the size (in Hectare, Ha) of all land plots operated or cultivated by the household. We note that the size of land plots is accurately measured by GPS or, in case of small fields, by compass and rope, while the size of the remaining land plots is reported by farmers.

Quality of land: Our data also contain detailed information on the quality of land for each plot used in each household. These data include elevation, slope, soil quality, erosion, terrain roughness, nutrient availability, nutrient retention, rooting conditions, oxygen availability to roots, excess salts, toxicity, and workability. The elevation (in meters) and slope (in meters) are continuous variables while the rest of land quality variables are categorical such as terrain roughness (plains, lowlands, plateaus, hills, mountains), erosion (1 none, 2 low, 3 moderate, 4 high), nutrient availability, nutrient retention, rooting conditions, oxygen availability to roots, excess of salts, toxicity and workability (1 constraint, 2 moderate constraints, 3 severe constraints and 4 very severe constraint). Then, we regress agricultural value added on all these dimensions of land quality, controlling for capital and labour input and take the coefficients from this regression to construct our benchmark land quality index for each farm, by following (Chen et al., 2021, 2023). For households with more than one plot, we take a weighted average of each of these dimensions using the size of plot as weight. The importance of this regression is to show that how these dimensions of land quality affect farm value added.

Capital: The measure of **capital** is a bit more complicated. The information on capital input in production is available in terms of quantities for implements (i.e., hand hoe, slasher, axes, pickaxes, sprayer, knife, sickle, treadle pump and watering can), machinery (e.g., ox cart, ox plough, tractor, tractor plough, ridger, generator, motorized pump, etc.) and capital services rented in and out. To measure the capital stock per item **in Nigeria and Tanzania**, we use the estimated current selling price of capital items ("*If you wanted to sell one of this ITEMS today, how much would you receive?*") after conditioning on its use ("*Did your household use the ITEM during the last 12 months?*") to measure capital. We construct the household agricultural capital stock by aggregating across all agricultural items and add capital services rented out and subtract and capital services rented in. While in **Ethiopia**, we observe the physical quantity of these tools or item owned by each household, as well as their prices at local markets and construct common prices, defined as the median of sell prices, to evaluate these the capital stock per items[26]. The richness of the Ethiopia Socioeconomic Survey (ERSS) is that it provides the three most common livestock, cattle, goats, and sheep, as well as their farm use. In our measure of capital stock, we only include cattle that are for agricultural or transportation purposes, and exclude goats and sheep, which are mainly used for meat, wool, or milk. We also observe the prices at which household farmers sell their cattle. Finally, we sum up the values of agricultural tools, transportation tools, and cattle as our measure of farm capital.

For those farmers who have zero capital, but report cultivated land and positive output, we follow (Adamopoulos et al., 2022) and impute for all farmers value equal to the amount of land operated by the household multiplied by 10% of the median of the median of the calculated capital value.

Other variables Household characteristics: The survey also includes a detailed section on household characteristics, the socio-demographic characteristics of members, etc.

Appendix B: Proof propositions

proposition 1:

Differentiating $l_i^*(s)$ with respect to s_i of Equation (5), yields:

$$\frac{\partial l_i^*(s)}{\partial s_i} = \gamma^{\frac{1}{1-\gamma}} \left(\frac{\alpha}{q}\right)^{\frac{1-\gamma(1-\alpha)}{1-\gamma}} \left(\frac{1-\alpha}{r}\right)^{\frac{\gamma(1-\alpha)}{1-\gamma}} > 0 \qquad \text{(B1)}$$

This implies that for all households who participate in rental markets, the land operated will increase with agricultural total factor productivity (s).

For households renting in, the amount of land rented in is the difference between the operational land (or cultivated land) and the land endowment:

$$land_{in} = l_i - \overline{l_i} \qquad \text{(B2)}$$

[26] The estimated current selling price of capital items is not available in the Ethiopian survey.

Totally differentiating both sides of equation (B2) with respect to s_i, yields: $\frac{\partial land_{in}}{\partial s} = \frac{\partial l_i}{\partial s} > 0$, this implies that for households who rent in land, the amount of land rented in will be increasing in agricultural productivity (s).

Totally differentiating both sides of equation (B2) with respect to $\overline{l}_i$, yields: $\frac{\partial land_{in}}{\partial \overline{l}_i} = -1 < 0$, this implies that for households who rent in land, the amount of land rented in is decreasing in land endowment.

For those households renting out[27], the amount of land rented out is the difference between the land endowment and the land operational:

$$land_{out} = \overline{l}_i - l_i \qquad \text{(B3)}$$

Totally differentiating both sides of equation (A3) with respect to s_i, yields: $\frac{\partial land_{out}}{\partial s} = -\left(\frac{\partial l_i}{\partial s}\right) < 0$, this implies that for those households who rent out land, the amount of land rented out will be decreasing in agricultural productivity (s). Differentiating equation (A3) with respect to $\overline{l}_i$, yields: $\frac{\partial land_{out}}{\partial \overline{l}_i} = 1 > 0$, this implies that for those households who rent out land, the amount of land rented out is increasing in land endowment.

Proof proposition 2

Totally differentiating both sides of Equation 7 and 8 with respect to T_i yields such that $l_i = l_i^*\left(s_i, T_i, q, r\right)$ and $k_i = k_i^*\left(s_i, T_i, q, r\right)$

$$\begin{pmatrix} \frac{\partial^2 \pi\left(s_i, T_i\right)}{\partial k_i \partial k_i} & \frac{\partial^2 \pi\left(s_i, T_i\right)}{\partial k_i \partial l_i} \\ \frac{\partial^2 \pi\left(s_i, T_i\right)}{\partial k_i \partial l_i} & \frac{\partial^2 \pi\left(s_i, T_i\right)}{\partial l_i \partial l_i} \end{pmatrix} \begin{pmatrix} \frac{\partial k_i}{\partial T_i} \\ \frac{\partial l_i}{\partial T_i} \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$

With some algebra with get:

[27]Note that we do not have data on rent out land. This may be due to survey design, which is based on arable land or cultivated land, including both owned and rented land; or farmers who rent out land are more likely to be excluded from the sample.

$$\frac{\partial l_i}{\partial T_{\mathrm{i}}} = 1 \Bigg/ \frac{\partial^2 f(.)}{\partial k_i \partial k_i}\left[\frac{\partial^2 f(.)}{\partial k_i \partial k_i} * \frac{\partial^2 f(.)}{\partial l_i \partial l_i} - \left(\frac{\partial^2 f(.)}{\partial k_i \partial l_i}\right)^2\right] < 0 \text{, since } \frac{\partial^2 f(.)}{\partial k_i \partial k_i} < 0 \qquad \text{(B4)}$$

This implies that household who rent in will cultivate less land as the transaction cost increases. Totally differentiating both sides of equation (8) with respect to T and rearranging terms yields:

$$\frac{\partial l_i}{\partial T_{\mathrm{i}}} = \frac{-1}{\frac{\partial^2 f(.)}{\partial k_i \partial k_i}\left[\frac{\partial^2 f(.)}{\partial k_i \partial k_i} * \frac{\partial^2 f(.)}{\partial l_i \partial l_i} - \left(\frac{\partial^2 f(.)}{\partial k_i \partial l_i}\right)^2\right]} > 0 \text{, since } \frac{\partial^2 f(.)}{\partial k_i \partial k_i} < 0 \qquad \text{(B5)}$$

This implies that households in the renting in pool will operate less land as the transaction cost increases.

For households who continue to rent in, the optimal operational land holding can be written as $l_i = l_i^*(s_i, T_i, q, r)$. Setting l_i to $\overline{l_i}$ yields the identity.

$$\overline{l_i} = l_i^*(s_u, T_i, q, r) \qquad \text{(B6)}$$

Totally differentiating both sides of equation (18) and rearranging terms yields,

$$\frac{ds_u}{dT_i} = -\frac{\partial l_i / \partial T_i}{\partial l_i / \partial s_i} > 0 \qquad \text{(B7)}$$

For $d\overline{l_i} = 0; \partial l_i / \partial s_i > 0$ from Equation (B1) and $\partial l_i / \partial T_i < 0$ from equation (B4). Equation (B7) implies that, as the transaction costs increase, more households would change from renting in land to autarky.

Similarly, for households who continue to rent out land, and based on equation (8), we have:

$$\frac{ds_l}{dT_i} = -\frac{\partial l_i / \partial T_i}{\partial l_i / \partial s_i} < 0 \text{ (For } \partial l_i / \partial T_i > 0 \text{ from equation (A5)} \qquad \text{(B8)}$$

Equation (B8) implies that more households would change from renting out to autarky as transaction costs increase.

We can similarly solve for the capital input which is also indirectly affected by the transaction costs T_i (land wedge).

Proof proposition 3

Consider the total output in zone z:

$$Y=\sum_{i=1}^{F} y_i=\sum_{i=1}^{F} s_i^{1-\gamma}\left(l_i^{\alpha} k_i^{1-\alpha}\right)^{\gamma}=\sum_i s_i^{1-\gamma}\left[\left(\frac{l_i}{L}\right)^{\alpha}\left(\frac{k_i}{K}\right)^{1-\alpha}\right]^{\gamma}\left(L^{\alpha} K^{1-\alpha}\right)^{\gamma}=A\left(L^{\alpha} K^{1-\alpha}\right)^{\gamma} \tag{B9}$$

Where $A=\sum_i s_i^{1-\gamma}\left[\left(\frac{l_i}{L}\right)^{\alpha}\left(\frac{k_i}{K}\right)^{1-\alpha}\right]^{\gamma}$ denotes aggregate TFP for zone z, implying that aggregate TFP depends not only on the households' TFP but also on how land and capital are allocated across households.

From equation (3), we have:

$$l_i=\left(\frac{\alpha\gamma}{q}\right)^{\frac{1}{1-\alpha\gamma}}\left(s_i\right)^{\frac{1-\gamma}{1-\alpha\gamma}}\left(k_i\right)^{\frac{\gamma(1-\alpha)}{1-\alpha\gamma}}=\left(\frac{\alpha\gamma}{q}\right)^{\frac{1}{1-\alpha\gamma}}\varphi_i\omega_i\left(k_i\right)^{\frac{\gamma(1-\alpha)}{1-\alpha\gamma}} \tag{B10}$$

Where $\varphi_i=\left(\frac{q}{q_i}\right)^{\frac{1}{1-\alpha\gamma}}$, q_i the equilibrium marginal value of land for household i, and $\omega_i=\left(s_i\right)^{\frac{1-\gamma}{1-\alpha\gamma}}$

Summarizing land cultivated area at zone level and calculating land share $\frac{l_i}{L}$ of households i, we have:

$$\begin{cases} L=\sum_i l_i=\left(\frac{\alpha\gamma}{q}\right)^{\frac{1}{1-\alpha\gamma}}\sum_i \varphi_i\omega_i\left(k_i\right)^{\frac{\gamma(1-\alpha)}{1-\alpha\gamma}} \\ \frac{l_i}{L}=\frac{\varphi_i\omega_i\left(k_i\right)^{\frac{\gamma(1-\alpha)}{1-\alpha\gamma}}}{\sum_i\left(\varphi_i\omega_i\left(k_i\right)^{\frac{\gamma(1-\alpha)}{1-\alpha\gamma}}\right)} \end{cases} \tag{B11}$$

Substitute the land share into the aggregate TFP (A) and with some algebra, we get:

$$A=\sum_i \frac{\omega_i\varphi_i^{\alpha\gamma}\left(k_i\right)^{\frac{\gamma(1-\alpha)}{1-\alpha\gamma}}}{\left[\left(\sum_i \omega_i\varphi_i\left(k_i\right)^{\frac{\gamma(1-\alpha)}{1-\alpha\gamma}}\right)^{\alpha}\right]^{\gamma}}\left(\frac{1}{K}\right)^{\gamma(1-\alpha)} \tag{B12}$$

Given that $\varphi_i \leq 1$, $\alpha,\gamma \in (0,1)$, $1-\alpha\gamma<1$, and from equation (A12), we have:

$$A \leq \sum_i \frac{\omega_i \varphi_i \left(k_i\right)^{\frac{\gamma(1-\alpha)}{1-\alpha\gamma}}}{\left[\left(\sum_i \omega_i \varphi_i \left(k_i\right)^{\frac{\gamma(1-\alpha)}{1-\alpha\gamma}}\right)^{\alpha}\right]^{\gamma}} \left(\frac{1}{K}\right)^{\gamma(1-\alpha)} = \sum_i \left(\omega_i \varphi_i \left(k_i\right)^{\frac{\gamma(1-\alpha)}{1-\alpha\gamma}}\right)^{1-\alpha\gamma} \left(\frac{1}{K}\right)^{\gamma(1-\alpha)} \tag{B13}$$

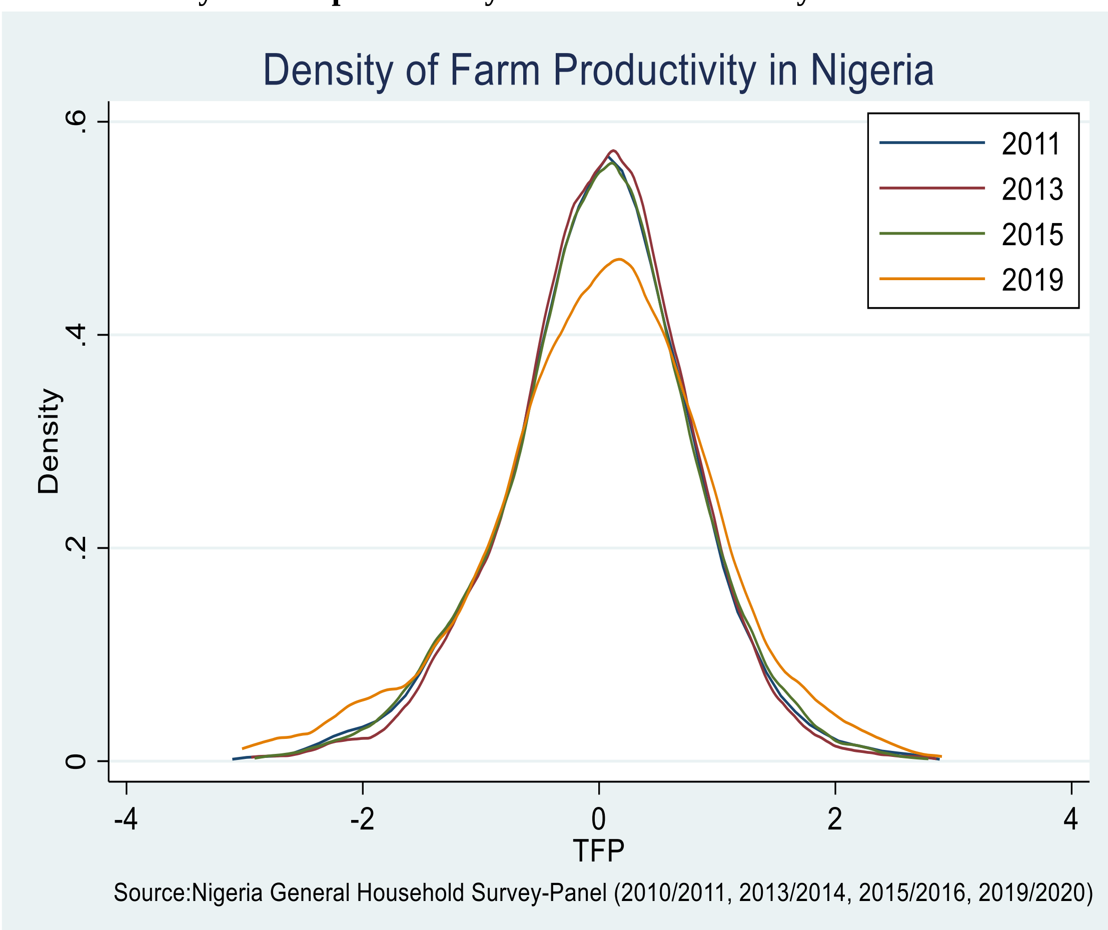
$$= \sum_i \left(\omega_i \varphi_i\right)^{1-\alpha\gamma} \left(\frac{k_i}{K}\right)^{\gamma(1-\alpha)}$$

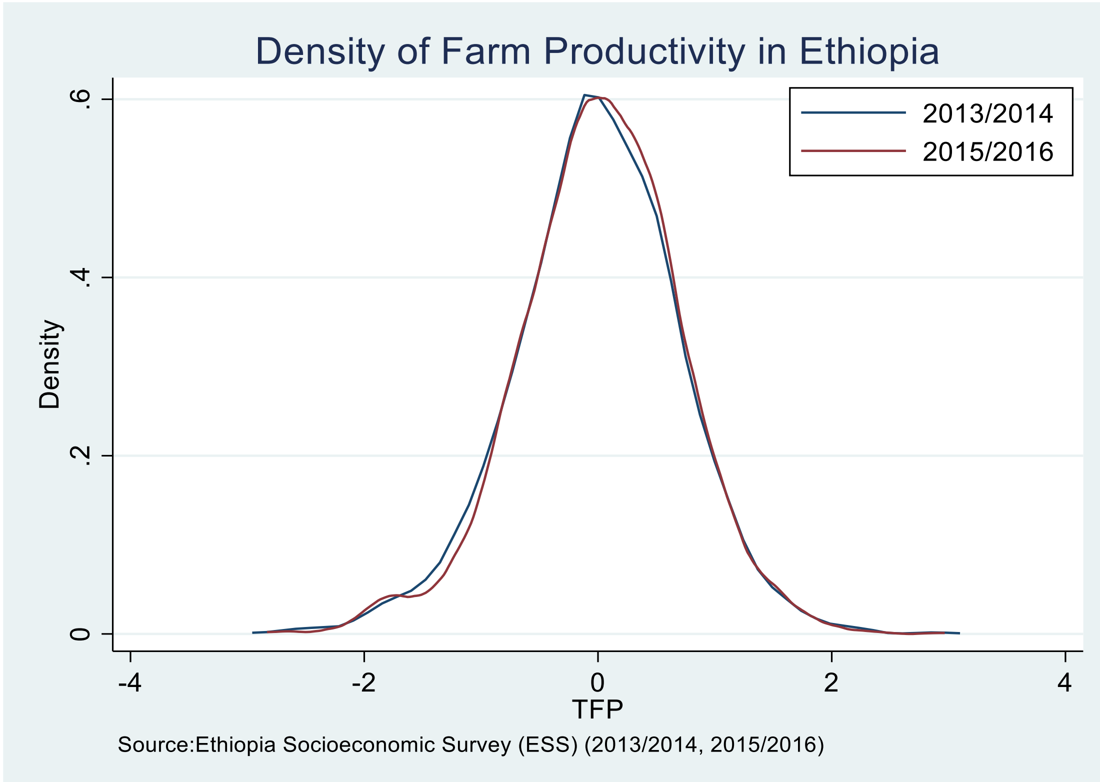
Note that $\left(\frac{k_i}{K}\right)^{\gamma(1-\alpha)} \leq 1 \; \forall i$ and $\varphi_i = \left(\frac{q}{q_i}\right)^{\frac{1}{1-\alpha\gamma}}$, therefore, we have:

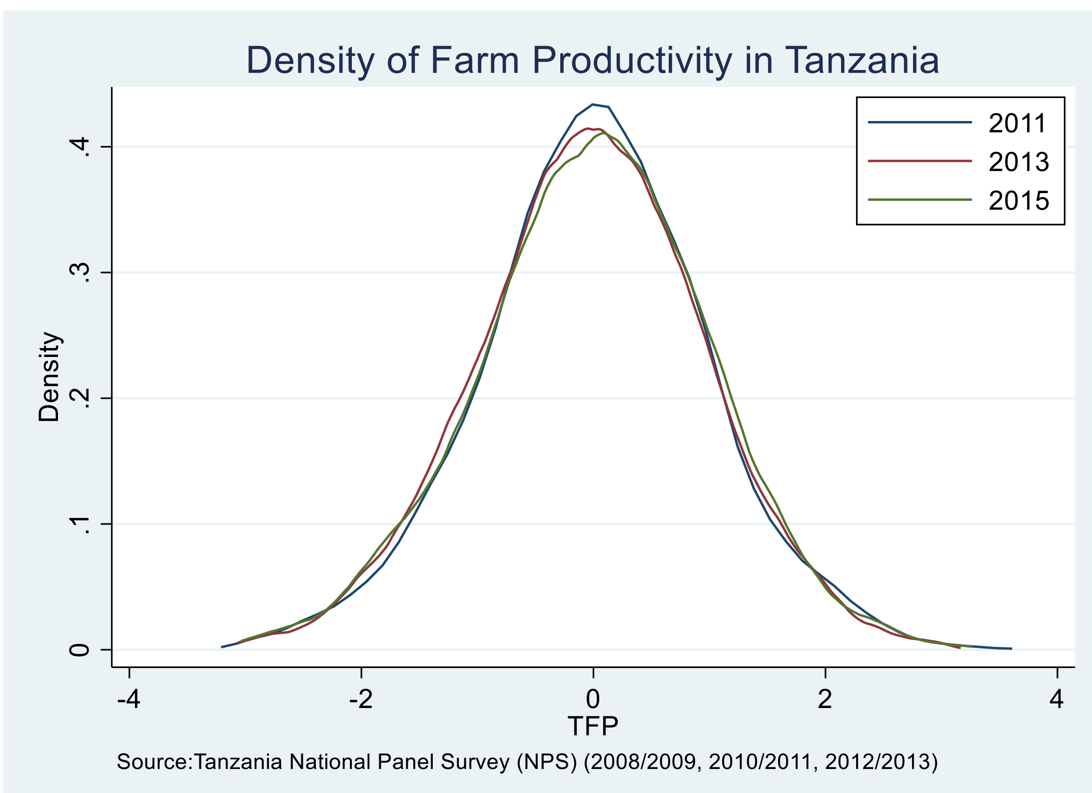
$$A_i = \sum_i \left(\omega_i \varphi_i\right)^{1-\alpha\gamma} \left(\frac{k_i}{K}\right)^{\gamma(1-\alpha)} \leq \sum_i \left(\omega_i \varphi_i\right)^{1-\alpha\gamma} \leq \sum_i s_i^{1-\gamma}\left(q = q_i\right) \tag{B14}$$

Equation (B14) shows that the aggregate TFP (A) increases when the transaction cost is removed $\left(T_i = 0,\; \varphi_i = 1\right)$, implying land certification will enhance the aggregate TFP and therefore zone level output.

Appendix C: density of farm productivity across countries and year




Density of Farm Productivity in Ethiopia
2013/2014
2015/2016
Density
0
.2
.4
.6
-4
-2
0
2
4
TFP
Source:Ethiopia Socioeconomic Survey (ESS) (2013/2014, 2015/2016)


Density of Farm Productivity in Tanzania
2011
2013
2015
Density
0
.1
.2
.3
.4
-4
-2
0
2
4
TFP
Source:Tanzania National Panel Survey (NPS) (2008/2009, 2010/2011, 2012/2013)

Appendix D: Tables

Table A1: Distribution of households' sample sizes

Country	Year of survey	No. of households in each wave	No. of household's farm in each wave
Nigeria	2010/11 (Wave 1)[28]	4916	2,301
	2012/13 (Wave 2)	4716	2,434
	2015/16 (Wave 3)	4581	2,626
	2018/19 (Wave 4)	4976	2,662
Ethiopia	2013/2014 (wave 1)	4954	2,844
	2015/2016 (wave 2)	5,469	2,547
Tanzania	2008/09 (Wave 1)	3,265	1,597
	2010/11 (Wave 2)	3924	2,020
	2012/13 (Wave 3)	5010	2,583

Source: author's computation, based on LSMS-ISA dataset

Appendix D: Correlation matrix between farm-level productivity, inputs productivity and factors inputs

Nigeria

Variables	(1)	(2)	(3)	(4)	(5)
(1) logSfei	1.00				
(2) logLfei	-0.04*	1.00			
(3) logKfei	-0.02	0.30*	1.00		
(4) logyol	0.85*	-0.49*	0.09*	1.00	
(5) logyok	0.39*	-0.11*	-0.91*	0.15*	1.00

**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Note: logSfei= Permanent farm level productivity, logLfei, logKfei represent Land and capital are measured relative to total labour days supplied to agriculture by the household, respectively. Logyol and logyok represent land and capital productivity, respectively.

[28] Keep in mind that this wave is used only for statistics descriptive and to calculate efficiency gain. We exclude this wave in our sample when estimate the effect of land certification on the outcomes (agricultural output, labour reallocation, and resource misallocation) since the wave does not report land property right.

Ethiopia

Variables	(1)	(2)	(3)	(4)	(5)
(1) logSfei	1.00				
(2) logLfei	0.03	1.00			
(3) logKfei	-0.14*	0.39*	1.00		
(4) logyol	0.81*	-0.52*	-0.11*	1.00	
(5) logyok	0.63*	-0.07*	-0.82*	0.38*	1.00

*** *p<0.01, ** p<0.05, * p<0.1*

Note: logSfei= Permanent farm level productivity, logLfei, logKfei represent Land and capital are measured relative to total labour days supplied to agriculture by the household, respectively. Logyol and logyok represent land and capital productivity, respectively.

Tanzania

Variables	(1)	(2)	(3)	(4)	(5)
(1) logSfei	1.00				
(2) logLfei	-0.03*	1.00			
(3) logKfei	0.00	0.33*	1.00		
(4) logyol	0.89*	-0.45*	0.01	1.00	
(5) logyok	0.59*	-0.07*	-0.77*	0.42*	1.00

*** *p<0.01, ** p<0.05, * p<0.1*

Note: logSfei= Permanent farm level productivity, logLfei, logKfei represent Land and capital are measured relative to total labour days supplied to agriculture by the household, respectively. Logyol and logyok represent land and capital productivity, respectively.

Appendix E: Efficient Allocation

Following Adamopoulos et al.,(2022), the planner chooses how to allocate land and capital across farmers in the rural village economy to maximize agricultural output subject to resource constraints. Specifically, the problem of the planner is[29]:

$$\max_{\{l_i, k_i\}_{i=1}^{F}} \sum_{i=1}^{F} s_i^{1-\gamma} \left(l_i^{\alpha} k_i^{1-\alpha} \right)^{\gamma} \qquad \text{(E1)}$$

Subject to

$$\sum_{i=1}^{F} l_i = L; \quad \sum_{i=1}^{F} k_i = K \qquad \text{(E2)}$$

Using the first order conditions of this this problem (Eq. D1 & D2), the efficient allocation involves allocating total land and capital across farmers according to relative productivity. Thus, the efficient allocations with superscript e are given by:

[29] We drop time and zone subscripts for convenience.

$$l^{e}\left(s_i\right)=\frac{s_i}{\sum_{i=1}^{F} s_i} L;\quad k^{e}\left(s_i\right)=\frac{s_i}{\sum_{i=1}^{F} s_i} K \tag{E3}$$

Farm output associated with the efficient allocation is: $y^{e}\left(s_i\right)=\frac{s_i}{\left(\sum_{i=1}^{F} s_i\right)^{\gamma}}\left[L^{\alpha} K^{1-\alpha}\right]^{\gamma}$ implying that in the efficient allocation, farm output is a linear function of farm productivity.

Using the definition of agricultural output $Y=\sum_{i=1}^{F} y_i$, we obtain zone level agricultural output under the efficient allocation,

$$Y^{e}=A^{e} F^{1-\gamma}\left[L^{\alpha} K^{1-\alpha}\right]^{\gamma} \tag{E4}$$

where $A^{e}=\left[\frac{1}{F}\sum_{i=1}^{F} s_i\right]^{1-\gamma}$ denotes efficiency agricultural TFP.

Following Hsieh and Klenow (2009) and Adamopoulos et al., (2022), we assume that misallocation manifest through distortions or wedges, which affect heterogeneous household in an idiosyncratic manner. These wedges may hinder heterogeneous household from achieving their optimal size, leading to aggregate TFP losses. So, we denote by τ_i^{l} and τ_i^{k} the land and capital input taxes, and by τ_i^{y} the output tax faced by farm i.

Given the distortions, the profit maximization problem facing farm i is:

$$\pi_i=\left(1-\tau_i^{y}\right) y_i-\left(1+\tau_i^{k}\right) r k_i-\left(1+\tau_i^{l}\right) q l_i \tag{E5}$$

where *q* and *r* are the rental prices of land and capital. In equilibrium, the land and capital markets must clear and is given by equation E2. Using the first order conditions with respect to land and capital for farm i imply:

$$MRPL_i=\alpha\gamma \frac{y_i}{l_i}=\frac{q\left(1+\tau_i^{l}\right)}{\left(1-\tau_i^{y}\right)} \propto \frac{\left(1+\tau_i^{l}\right)}{\left(1-\tau_i^{y}\right)} \tag{E6}$$

$$MRPK_i=(1-\alpha)\gamma \frac{y_i}{k_i}=\frac{r\left(1+\tau_i^{k}\right)}{\left(1-\tau_i^{y}\right)} \propto \frac{\left(1+\tau_i^{k}\right)}{\left(1-\tau_i^{y}\right)} \tag{E7}$$

Where MRPL and MRPK are the marginal revenue products of land and capital, respectively.

Equation D6 and D7 show that without farm-specific distortions, average products and marginal products of land and capital are equalised across farms at factors prices (r and q), which mean that the capital-land ratio is equalised across farms. However, in the presence of farm-specific distortions, average products and marginal products of land and capital are not equalized across farms, but rather vary in proportion to the idiosyncratic distortion faced by each factor relative to the output distortion.

It is straightforward to show that farm revenue productivity (TFPR) relate to the wedges or taxes and it can be written as:

$$TFPR_i = \frac{y_i}{l_i^{\alpha} k_i^{1-\alpha}} \equiv \left(\frac{q}{\alpha\gamma}\right)^{\alpha} \left(\frac{r}{(1-\alpha)\gamma}\right)^{1-\alpha} \frac{\left(1+\tau_i^l\right)^{\alpha}\left(1+\tau_i^k\right)^{1-\alpha}}{\left(1-\tau_i^y\right)} \qquad \text{(E8)}$$

Equation (6) shows that TFPR is proportional to a geometric average of the farm's marginal revenue products of capital and labour or a geometric average of the farm specific land and capital distortions relative to the output distortions:

$$TFPR_i \propto \left(MRPK_i\right)^{\alpha} \left(MRPL_i\right)^{1-\alpha} \propto \frac{\left(1+\tau_i^l\right)^{\alpha}\left(1+\tau_i^k\right)^{1-\alpha}}{\left(1-\tau_i^y\right)} \qquad \text{(E9)}$$

Using the definition of total output $Y = \sum_{i=1}^{F} y_i$, we can now derive the zone level agricultural output production:

$$Y = TFP.\, F^{1\text{-}\gamma} \left[L^{a} K^{1-\alpha}\right]^{\gamma} \qquad \text{(E10)}$$

Where (L, K) are the total land and capital and TFP is the zone level TFP, which is given by

$$TFP = \left[\frac{\sum_{i=1}^{F} s_i \left(\frac{\overline{TFPR}}{TFPR_i}\right)^{\frac{\gamma}{1-\gamma}}}{F}\right]^{1-\gamma} \qquad \text{(E11)}$$

Where $\overline{TFPR}$ is the average revenue productivity: $\overline{TFPR} = \frac{\left(\frac{q}{\alpha\gamma}\right)^{\alpha}\left(\frac{r}{(1-\alpha)\gamma}\right)^{1-\alpha}}{\left[\sum_{i=1}^{F}\frac{y_i}{Y}\frac{\left(1-\tau_i^y\right)}{\left(1+\tau_i^l\right)}\right]^{\alpha}\left[\sum_{i=1}^{F}\frac{y_i}{Y}\frac{\left(1-\tau_i^y\right)}{\left(1+\tau_i^k\right)}\right]^{1-\alpha}}$.

Equations D10 shows that without dispersion in $TFPR_i$ across households (i.e , if $\tau_{ijt}^{k} = \tau_{ijt}^{l} = 0$ and $\overline{TFPR} = 1$) the equilibrium allocation, aggregate output, and TFP coincide with the corresponding efficient statistics.

Efficiency gains: the efficiency gains from eliminating misallocation are given by the ratio of the efficient (Eq. E4) to the (distorted) observed total output (Eq. E9) minus one:

$$Effgains = 100 * \left(Y^{e}/Y^{*} - 1\right) \qquad \text{(E12)}$$

Equation (E12) represents the efficiency gain of relocating resources in a zone level and is a measure of misallocation.