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IFPRI Discussion Paper 01871

October 2019

Geography of Smallholders' Tractor Adoptions and R&D–Induced Land Productivity

Evidence from Household Survey Data in Ghana

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Abstract

Despite the urbanization and gradual rise of medium-to-large scale farming sector, smallholders without substantial mechanization remain central to agriculture in countries like Ghana. Significant knowledge gaps exist on the adoptions of agricultural mechanization among smallholders for whom the scope for exploiting complementarity with land is limited. We test the hypotheses that high-yielding technologies, which potentially raise total factor productivity and also returns to more intensive farm power use, are important drivers of adoptions of agricultural mechanization among smallholders. Using the three rounds of repeated cross-sectional, nationally representative data (Ghana Living Standard Surveys 2006, 2013, 2017), as well as unique tractor-use data in Ghana, and multi-dimensional indicators of agroclimatic similarity with plant-breeding locations, this paper shows that the adoption of rented agricultural equipment and tractors in Ghana has been induced by high-yielding production systems that have concentrated in areas that are agroclimatically similar to plant-breeding locations. These effects hold for mechanization adoptions at both extensive margins (whether to adopt or not) and intensive margins (how much to adopt). These linkages have strengthened between 2006 and 2010s, partly due to improved efficiency in supply-side factors of mechanization.

Keywords: agricultural mechanization, agroclimatic similarity, complementarity, adoption intensity, principal component-based instrumental variables, Ghana

Acknowledgments

We gratefully acknowledge funding support from Syngenta Foundation for Sustainable Agriculture and the CGIAR Research Program on Policies, Institutions, and Markets (PIM). The views expressed in this paper are those of authors and do not necessarily reflect those of their respective institutions. All remaining errors or omissions are our own.

1 Background

Recent economic growth and urbanization in parts of Africa South of Sahara (SSA), including West African countries like Ghana, have spurred interests among policymakers and stakeholders regarding how to promote mechanization of the agricultural sector where, unlike the rest of the economy, the productivity growth and use of modern machine remains low (Diao et al. 2016; Malabo Montpellier Panel 2018).

There is a growing narrative about the labor-substitution, and land expansion motives of mechanization in SSA and elsewhere. However, despite relatively larger farm sizes compared to Asia, SSA is still largely smallholder-dominated from global perspectives. Where mechanization has grown within SSA, it has occurred as a large number of relatively small farmers renting in agricultural machines from owners of these machines, patterns which have been widely observed in Asia in recent decades. Despite the gradual growth of medium-to-large farmers (Jayne et al. 2016), in SSA, smallholders are likely to continue accounting for the significant share among adopters in the short- to medium- terms.

One of the under-studied aspects is the role of yield potential in the adoption of mechanical technologies. Hypothetically, in the land-scarce environment, a rise in total factor productivity (TFP) often represented by biological technologies like improved varieties (Evenson & Gollin 2003; Walker & Alwang 2015) still enhance the returns to, and demand for, more intensive power use per unit of land in farming. Furthermore, development of biological technologies in developing countries remain largely in the public-sector domain, because of high risks and long- maturation periods involved with R&D on biological technologies, and thus not easily induced by the market conditions, constituting an important source of exogenous variation in agricultural productivity (Takeshima 2018). In addition, the gap between Asia and SSA in national agricultural R&D capacity, has been correlated with the gap in mechanization adoption levels between the two regions, again pointing toward the potential roles of yield-enhancing biological technologies in mechanization adoption.

Another issue, which is particularly important for the case of mechanization adoption among smallholders, is the adoption intensity (intensive margins). Agricultural machinery that is typically used through custom-hiring mechanisms, like tractors, are characterized by indivisibility and limited spatial mobility in SSA countries (Takeshima et al. 2015). At the same time, smallholders are spatially scattered, with variable timing of land preparation due to the diversity of farming systems, and often limited incentives to coordinate with neighboring farmers to aggregate the demand for mechanized land preparation that can potentially attract custom-hiring service providers. In such environment, the spread of the use of agricultural machinery through rentals, may be driven more by the greater demand at intensive margins (how much to rent in), not only at extensive margins (whether to rent in or not), by individual smallholders. This may be more so than other inputs like fertilizer, that are more divisible. The knowledge gaps remain, however, regarding what induces greater adoption at intensive margins.

This paper aims to partly fill these knowledge gaps, by using the case of Ghana. Ghana offers an interesting setting to investigate these issues. It is one of the SSA countries with fast urbanization and significant labor movement into the non-agricultural sector, and yet slow modernization of the agricultural sector.[1] Ghana has also allowed relatively free importation of

[1]According to GDCC (2018), the share of workers employed in the agricultural sector in Ghana has declined to 40 percent by early 2010s, similar to many countries in Asia today. However, yields of maize and rice have remained around 2 tons / ha, and 2.8 tons / ha, respectively, as of 2017, considerably lower than Asian counterparts (FAOSTAT 2018).

tractors (among which used-tractors account for the majority of imported tractors) (Diao et al. 14), allowing the private sector investments in machines to respond significantly to the spatial variations in the returns.[2]

Using the three rounds of repeated cross-sectional, nationally representative data (Ghana Living Standard Survey 2006, 2013, 2017), supplemented by detailed data on tractor use in Ghana (IFPRI-SARI survey 2014), as well as multi-dimensional indicators of agroclimatic similarity that capture the exogenous variations in spillover potentials of high-yielding biological technologies, we investigate how farm-household'-level adoption of rented agricultural equipment (both at extensive and intensive margins) respond to the farm-household-level variations in yields. Our results suggest that the adoptions of rented machines are positively associated with higher yield, as well as greater agroclimatic similarity with plant-breeding locations within the country, that indicates greater spillover potentials of high-yielding biological technologies, and these hold for both at extensive and intensive margins.

This paper contributes to the literature in several ways. First, the paper contributes to the growing literature on agricultural mechanization in SSA countries including Ghana (Pingali 2007; Kienzle et al. 2013; Diao et al. 2014; Takeshima et al. 2018) by providing evidence on the various determinants of machine adoptions from both demand and supply sides. Second, the paper contributes to the conventional literature on agricultural technology adoption by providing evidence on the determinants of adoption at intensive margins. Third, by focusing on the role of yield-enhancing technologies on capital deepening in the agricultural sector, our paper contributes to the broader literature on the roles of high-yielding technologies on economic transformation (Bustos et al. 2016; McArthur & McCord 2017; Gollin et al. 2018). In investigating the role of yield-enhancing technologies, the paper also contributes to the growing literature based on the similarity of agroclimatic conditions across locations (Bazzi et al. 2016; Takeshima 2019). Fourth, in constructing and using aforementioned agroclimatic similarity indicators in the analyses, the paper contributes to the econometrics literature on factor analyses and instrumental variable analyses (Kloek & Mennes 1960; Amemiya 1966; Stock & Watson 2002; Bai & Ng 2010; Kapetanios & Marcellino 2010; Emran & Hou 2013).

This paper is structured as follows. Section 2 briefly discusses the potential linkages between yield-enhancing technologies and mechanization use intensity. Section 3 briefly describes mechanization and plant-breeding in Ghana. Section 4 presents the data and descriptive statistics. Section 5 describes the estimation methods. Section 6 discusses the results, while section 7 concludes.

2 Yield-enhancing technologies and mechanization use intensity

Our primary hypothesis is that the introduction of yield-enhancing technologies, including high-yielding varieties, raises returns to more intensive use of agricultural machines, especially for smallholders who would otherwise not gain from machine adoptions due to the limited scope for them to exploit scale economies through mechanization. While it is beyond the scope of this paper to test exact agronomical linkages, we briefly discuss here the potential mechanisms that may lead to observed complementarity between yield-enhancing technologies

[2] The significant ability of the private sector to respond to market condition has also been demonstrated in the recent experiences in Ghana. While the public sector has intervened in the mechanization service market through various programs including the recent AMSEC program (Benin 2015), these public-sector efforts have often been less effective than purely private-sector led mechanization service provision, because of the relative inefficiency of public-sector selected service providers (Diao et al. 2014; Diao et al. 2018).

and mechanization adoption, especially adoption at intensive margins which have not been studied extensively in the literature.

One of the primary channels of such complementarity may be tillage operations. Tillage (or plowing) is often used to change the soil properties, by changing the porosity, improving aeration, root penetration, water infiltration, reducing evaporation (Pingali et al. 1987; Ehui & Polson 1993; Windmeijer & Andriesse 1993), and incorporation of crop residues, manure, among others (Richerson, 2001). Some tillage is done for weed control purpose (Moorman & Breemen 1978), although tillage for this purpose may require significant intensity because the effectiveness differs by types of weeds (Rodenburg & Johnson 2009). Where multiple tillages are practiced, primary tillage is used to break up the soils, while subsequent tillage may be used to remove clods and prepare optimal seedbed (Carranza 2014), level fields to improve the efficiency of subsequent operations (water management, uniform harvesting, etc.).

Overall, among factors that affect yield, tillage is one of the operations that affect attainable yield (Tittonell & Giller 2013). In theory, many of the aforementioned objectives of tillage are to raise the productivity of improved varieties that typically respond well to these practices. For example, operations to alter soil properties may generally allow providing more water to varieties that have been bred to respond to more intensive water application. They may also provide more nutrients to varieties that have been bred not to lodge easily after plant growth (e.g., dwarf varieties). Tillage for weed control may also enable planting fertilizer-responsive varieties and intensive use of fertilizer, which would otherwise also induce weed growth.

In Asia, where the use of tractors has spread considerably among smallholders, tillage intensity has been high historically. For example, before the take-off of tractor use growth in each Asian country, the intensity of animal traction use per unit of land had been often significantly high, compared to the level in West African countries like Nigeria today (Takeshima & Lawal 2018). These patterns are also consistent with the hypotheses that improved varieties (which have been more developed in Asia) have raised returns to more intensive tillage and induced mechanization adoptions among smallholders.

3 Agricultural mechanization and agricultural R&D in Ghana

Agricultural mechanization in Ghana

Similar to many African countries, the use of agricultural equipment like tractors in Ghana initially grew through active promotions in the 1970s (Wiemers 2015), but had stagnated since the 1980s when the Structural Adjustment Program (SAP) led to the significant devaluation of Ghanaian currency and increased prices of imported capital goods like tractors.

Since the 2000s, Ghana has started seeing the re-emergence of mechanization, as the continuous population growth led to shortened fallow period and farming system intensification, and economic transformation led to rising farm labor costs (Diao et al. 2014). In 2006, Ghana had about 3,000 tractors (World Bank 2012). Since then, by 2012, additional 4000 ~ 6000 tractors had been imported by the government and the private sector combined (Diao et al. 2012; Houssou et al. 2016), so that by 2012, the total number of tractors in the country was likely to have grown substantially.

During this time, however, the significant shares of smallholder farms have remained in the agricultural sector. For example, while the share of farms cultivating less than 5ha (10ha) of land has declined from 92 (97) percent in 1992, the share still remained high at 85 (94) percent in 2012 (Jayne et al. 2016). Similarly, the areas cultivated by these smallholders less than 10 ha, still accounted for 68 percent of all farm area in 2012, although it had declined from 78 percent in 1992 (Jayne et al. 2016). Given that smallholders still account for a significant majority of farms in Ghana, mechanization growth since the 2000s had involved significant growth of adoptions among smallholders, and future mechanization growth is likely to involve similar patterns at least in the short-to-medium terms. However, unlike large-farms for whom motive for mechanization is clearer (e.g., scale economies), motives for smallholders have remained unclear.

Agricultural R&D / plant breeding in Ghana

As in many developing countries, the public-sector R&D institutions have led plant breeding activities in Ghana (Lynam et al. 2016). Research toward genetic improvement (including germplasm conservation, breeding, molecular biology, tissue culture, etc.) has accounted for a significant share of agricultural R&D in Ghana.[3] Much of plant breeding activities in Ghana, as in other parts of Africa, have focused on yield-enhancement (Walker & Alwang 2015). This is because the majority of modern germplasms that are provided by international agricultural research centers, which Ghana has used for in-country testing or adaptive breeding, have originally been bred for yield-enhancement objectives. Shifts in focus toward other traits like drought tolerance have begun only recently.

In recent decades, public-sector plant breeding activities have been led by International Institute of Tropical Agriculture (IITA), as well as institutions under The Council for Scientific and Industrial Research (CSIR), including Crop Research Institute (CRI), Savannah Agricultural Research Institute (SARI), and Animal Research Institute (ARI), Oil Palm Research Institute (OPRI), and Plant Genetic Resources Research Institute (PGRRI).[4] These institutes have several experiment stations across the country, as summarized in Table 1, where potential varieties are evaluated for their performances. While plant breeding activities may be conducted outside CSIR, because of collaborative nature, these varieties are also typically evaluated in these experiment stations.

[3]For example, in Ghana in 2009, full-time equivalent staff engaged in these activities accounted for close to half of all activities (Walker & Alwang 2015).

[4]Other institutes under the CSIR conduct little plant breeding, but rather focus on other issues like forestry, food safety, or industrial research, and therefore excluded in our analyses.

Table 1. Locations of plant-breeding institutes/outstations in Ghana

Locations	International Institute of Tropical Agriculture (IITA)	Crop Research Institute (CRI)	Savanna Agricultural Research Institute (SARI)	Animal Research Institute (ARI)	Oil Palm Research Institute (OPRI)	Plant Genetic Resources Research Institute (PGRRI)
Accra	x					
Akumadan		x				
Assin Fosu		x				
Aiyinase		x				
Babile				x		
Bunso						x
Demon-Chegbani				x		
Ejura		x				
Fafraha				x		
Fumesua		x				
Kpeve		x				
Kpong		x				
Kusi					x	
Manga			x			
Nyankpala			x	x		
Ohawu		x				
Pokuase		x		x		
Tamale	x					
Wa			x			

Source: Authors' compilations.

Varieties that have been evaluated at these experiment stations and later released, have often accounted for a significant share of total cultivated areas. For example, rice varieties like Jasmine 85, Togo Marshall, which were tested at Kpong Research Station (Takeshima et al. 2013), have accounted for almost 40% of rice area in Ghana in 2011, outperforming indigenous varieties (Walker & Alwang 2015). These patterns are consistent with our hypothesis that yield potentials within Ghana may depend on the similarity of agroecological environments with these plant breeding stations.

4 Data and descriptive statistics

Our analyses use two set of datasets. First set of data are Ghana Living Standard Survey data (GLSS) from the 5th (2005/06), 6th (2012/13) and the 7th (2016/17) rounds, which are repeated cross-section data and nationally representative in respective years. Details of data are in Ghana Statistical Service (2018). GLSS 5 was sampled based on a two-stage sampling procedure. In the first stage, 580 enumeration areas (EAs) were selected based on the 2000 population census based on the probability that is proportional to the number of households, and 15 households were randomly selected from each of these EAs. For GLSS 6 and GLSS 7, the number of EAs increased to 1,200 and 1,000 respectively, from which 15 households per EA were randomly selected.

The second set of data is from mechanization survey conducted by IFPRI and Savannah Agricultural Research Institute (SARI) in 2013 (IFPRI-SARI data) (IFPRI/SARI 2014). IFPRI-SARI data complement GLSS by providing more specific information of tractor use and its intensity, and supply of tractor hiring services, neither of which is captured in GLSS, although IFPRI-SARI data have a smaller sample size, and cover more medium- and large-scale farmers.

Details of the data are in Chapoto et al. (2014). We use analyses based on IFPRI-SARI data to supplement the main analyses on GLSS, and show that the results from the latter analyses may, in fact, largely reflect tractor uses for tillage.

In addition, we also use agroclimatic spatial data from various sources. Soil-related information is obtained from FAO et al. (2012). Historical averages of rainfall data between 1980 and 2006 come from CRU (2017a), while wind-data are from CRU (2017b). Elevation, slope and topography are obtained from The United States Geological Survey (USGS) (1996), and terrain ruggedness index is calculated following Riley et al. (1999). Euclidean distance to the nearest major river is calculated using Lehner et al. (2006). These agroclimatic data are used to construct an indicator of agroclimatic similarity, described in a later section.

In our analyses, all monetary values are converted into real values, using the price indices reported in each round of GLSS, to account for the variations in living costs across EAs. Specifically, figures are expressed as Ghana cedi, and deflated by the ratio of price levels in each EA to those at the national averages in each of 2006, 2013 and 2017. For IFPRI-SARI data, since price index is not reported, we use the local price of maize to denominate all monetary values.

4.1 Descriptive statistics of primary sample of analyses

Table 2 presents the descriptive statistics among the primary samples in GLSS, which are households engaged in farm production in each year. Households are mostly male-headed with an average of five household members. Household heads typically have four years of formal education. The adoptions of modern inputs have gradually increased over time, albeit slowly. The EA shares of fertilizer users in areas where these farm households resided had increased from about 20 percent to 35 percent between 2006 and 2017, while tractor owners in the same areas increased from about 1.5 percent to 5 percent. Land fragmentation decreased from 2006 to 2013, but increased from 2013 to 2017.

Table 2. Descriptive statistics (among farm households) - GLSS

Variables	2005/06		2012/13		2016/17		Total	
	mean	Std.dev	mean	Std.dev	mean	Std.dev	mean	Std.dev
Rent in machines (yes = 1)	.06	.24	.17	.38	.18	.38	.15	.36
Distance to road / public transportation (km)	1.97	4.70	2.65	5.32	1.90	3.86	2.24	4.74
Distance to market (km)	6.37	7.54	9.50	9.91	8.10	9.44	8.33	9.35
Distance to extension office (km)	9.01	12.35	10.16	13.03	12.15	13.91	10.59	13.25
Distance to PBI (Geographic minutes)	.51	.29	.50	.34	.51	.32	.51	.33
Household size	5.10	3.07	5.16	3.05	5.27	3.23	5.19	3.12
Age of head	47.11	15.15	48.17	15.57	48.55	15.46	48.06	15.45
Gender of head (female = 1)	.19	.39	.19	.39	.21	.41	.20	.40
Education of head (years)	3.91	4.50	4.16	4.57	4.17	4.77	4.11	4.63
Farmland owned (ha)	4.12	22.97	2.97	19.17	3.58	26.01	3.43	22.55
Livestock (value, 1000)	1.18	11.15	1.81	12.20	2.09	13.55	1.77	12.46
Non-productive assets (value, 1000)	6.67	53.49	6.53	114.38	12.09	201.68	8.46	142.30
Agricultural capital (value, 1000)	.12	1.32	.20	2.12	.42	7.11	.25	4.43
Non-farm enterprise asset (value, 1000)	.14	1.49	.19	4.57	.63	18.11	.33	11.03
Farm wage (male wage per day)	1.78	.86	8.34	7.79	17.05	10.45	9.86	9.85
Land value per hectare (value, 1000)	1.15	2.35	1.00	2.01	2.32	15.99	1.48	9.53
EA sample share of irrigators (max = 1)	.004	.032	.009	.044	.011	.064	.009	.052
EA sample share of fertilizer users (max = 1)	.25	.28	.40	.35	.40	.34	.37	.34
EA sample share of tractor owners (max = 1)	.03	.17	.08	.27	.08	.27	.07	.25
Land fragmentation index (max = 1)	.43	.38	.51	.41	.40	.46	.45	.42
Number of observations	3,663		7,209		5,645		16,517	

Source: Authors.

Note: "Value" = Cedi deflated by Consumer Price Index with Accra = 1.
Exchange rate between Cedi – USD; USD 1 = GHC 0.917 (2006), GHC 1.954 (2013), GHC 4.351 (2017) (USDA 2019).

Table 3 summarizes the distribution of own farm size (ha) in each round of GLSS. Most of the sample farm households are smallholders, owning less than 10 ha of land.

Table 3. Percentile distribution (ha) of own farm land (among farm households)

Year	Do not own (%)	Percentile 10	20	30	40	50	60	70	80	90
2006	51.6	0.8	1.2	1.2	1.6	2.1	2.8	4.0	5.3	8.9
2013	44.3	0.8	1.2	1.6	2.0	2.4	3.2	4.0	5.3	8.1
2017	35.7	0.6	0.8	1.2	1.6	2.0	2.4	3.3	4.6	8.1
Among machine adopters (renting equipment or owning tractors)										
2006	53.3	0.8	1.2	1.6	2.2	3.2	4.0	4.9	8.1	12.3
2013	28.4	1.1	1.6	2.0	2.6	3.2	4.0	4.9	6.5	10.1
2017	19.4	0.8	1.2	1.6	2.0	2.8	3.6	4.1	6.1	8.1

Source: Authors' calculations from GLSS.

Table 4 summarizes the statistics of agroclimatic variables used. Most of the sample households are in areas with about 1,000 mm of annual precipitation. The standard deviations of various agroclimatic variables indicate that, among these households, there are significant variations in production environments, particularly in soil types and topography. While overall variations are somewhat modest for other agroclimatic variables, these variables in some areas deviate considerably from the rest of the country.

Table 4. Agroclimatic variables

Variables	mean	Std.dev
Rainfall (mm)	1097.107	123.609
Wind (meter per second)	1.284	.233
Drainage (poor, %)	17.753	24.562
Drainage (excessive, %)	1.274	4.384
Sodicity of soil (%)	1.862	.612
Salinity of soil (deciSiemens per metre)	.112	.095
Coarse texture in the soil (%)	17.272	27.837
Fine texture in the soil (%)	7.305	14.730
Organic content (% of soil weight)	.894	.183
Soil acidity (pH)	5.845	.754
Elevation (m)	210.063	72.669
Terrain ruggedness (index)	1.824	3.337
Slope (%)	.566	.495
Euclidean distance to the nearest river (Geographic minutes)	.018	.002

Source: Authors.

Descriptive statistics of IFPRI-SARI data

Table 5 summarizes the descriptive statistics of IFPRI-SARI data. As IFPRI-SARI data are purposively selected, the sample characteristics somewhat differ from Table 2. For example, the primary sample of rice growers in IFPRI-SARI data comprise more large households that are headed by males who are less educated, households that have more farm land, agricultural and livestock assets, that reside in areas where irrigation and tractor ownership are relatively more common, than among GLSS samples. Tractor users are also significantly more represented in IFPRI-SARI data.

Table 5. Descriptive statistics of IFPRI-SARI data (rice growers)

Variables	Total farm size < 20 ha		Total farm size < 10 ha	
	mean	std.dev	mean	std.dev
Use tractors (yes = 1)	.655	.476	.563	.497
Frequency of tractor-tillage	.738	.678	.619	.672
Distance to the nearest towns with 20,000 population (hours)	1.695	.743	1.641	.728
Government is the main source of extension service	.436	.497	.397	.490
Distance to the nearest PBI (Geographic minutes)	.474	.358	.464	.367
Household size	9.701	5.066	9.163	4.782
Age of head	44.475	14.110	43.798	14.125
Gender of head (female = 1)	.153	.360	.218	.414
Education of head (years)	2.626	4.645	2.579	4.529
Farmland owned (ha, natural log)	2.052	.605	1.721	.471
Livestock (value, natural log)	6.518	3.384	6.131	3.427
Non-productive assets (value, natural log)	7.359	2.296	6.907	2.431
Agricultural capital (value, natural log)	7.460	2.376	6.945	2.463
Daily farm wage (value, natural log)	3.882	.387	3.916	.384
Land tenure security (share of land that can be left without losing it)	.844	.341	.834	.348
Village sample share of irrigators	.149	.254	.169	.260
Fertilizer price per kg (natural log)	.024	.337	.054	.387
Village sample share of tractor owners	.140	.238	.082	.161
Land fragmentation index	.685	.149	.684	.153
Region (Ashanti)	.073		.068	
Region (Brong Ahafo)	.081		.079	
Region (Northern)	.275		.194	
Region (Upper East)	.512		.619	
Region (Upper West)	.060		.040	
Number of observations	382		250	

Source: Authors.
"Value" is denominated equivalent to kg of local staple crops, which is maize.

4.2 Key patterns of agricultural mechanization in Ghana

GLSS data aggregate all the expenses on rented agricultural equipment, instead of disaggregating the expenses into different equipment. Therefore, analyses based on GLSS focus on renting-in of all agricultural equipment combined. We, however, can expect that much of these expenses are on tractors, based on the information from equipment owners which report the total revenues from renting out each type of agricultural equipment. Table 6 summarizes the share of rental revenues that originate from various agricultural equipment including tractors and their attachments, calculated from GLSS. In 2006 and 2013 rounds, more than 80 percent of total revenues originated from tractors and their attachments. While this share dropped slightly in 2017, still about 2/3 of total revenues originated from tractors and their attachments. This makes sense because, for smallholders that account for most samples, tractors are some of the most expensive machinery and can be only rented, while other small machines can be owned.

Table 6. Share of each equipment among hiring out revenues[a]

Equipment	GLSS 5 (2006)		GLSS 6 (2013)		GLSS 7 (2017)	
	No. observations	Share (%)	No. observations	Share (%)	No. observations	Share (%)
Tractors	5	77.8	53	54.3	83	54.5
plough	5	0.2	44	16.8	25	7.0
trailer / cart	18	7.0	20	13.3	8	0.2
other tractor drawn equipment	1	0.0	3	4.5	5	1.8
Tractor and attachments		**85.0**		**88.9**		**63.5**
Other animal drawn equipment	24	6.0	13	0.8	21	0.6
Harvester	0	0.0	4	1.5	1	0.1
Spraying machine	41	4.3	101	5.6	105	12.9
Water pumping machine	0	0.0	9	0.8	16	21.5
Outboard motor	1	0.2	1	0.0	1	0.3
Canoe	4	2.1	4	0.7	4	0.3
Fishing net	4	0.3	4	0.8	0	0.0
Protective clothing / safety equipment	0	0.0	1	0.0	5	0.1
Others	1	2.0	1	0.8	12	0.6
Total	104	**100.0**	258	**100.0**	298	**100.0**

Source: Authors based on GLSS data.
[a]Figures are adjusted using sample weights.

Table 7 summarizes the share (%) of farm households renting in agricultural machines, disaggregated by regions,[5] in 2006, 2013 and 2017. Nationwide, the share has increased slightly from 6.2% in 2006 to 12.9% in 2013 and 14.1% in 2017. The growth speeds have been heterogeneous across regions, with Northern and Upper West regions exhibiting faster growth, both reaching about 30 percent in 2013. The intensity of machine rental, measured as the rental expenditure (Cedi per year), also varies across regions. The rental intensity had been higher in Northern and Upper West regions as of 2006, with the median of about 300 ~ 346 Cedi / year (or about 101 ~ 148 cedis/ ha, year), compared to the national level median of 90 Cedi / year. However, the shares (%) in these two regions in 2006 had not been very different from the national level share of 6.2%. In 2013, the median values of expenses declined in these two regions, largely due to the significant increase of low-intensity adopters, but remain higher than in other regions. These patterns suggest that while the adoptions at extensive and intensive margins are correlated with each other, they may be affected by different factors. These patterns also motivate further analyses.

[5]Regions in Ghana are shown in Appendix.

Table 7. Share (%) of farm households renting in agricultural machines, by regions[a]

Regions	% of farm households renting in equipment			Median of expenditure on rental (cedi / year)			Median of expenditure on rental per ha of cultivated area (cedi / ha, year)[b]		
	2006	2013	2017	2006	2013	2017	2006	2013	2017
Western	10.9	15.5	11.2	80	50	120	21	15	31
Central	2.3	1.9	6.9	50	24	80	9	12	46
Greater Accra[c]	6.4	10.1	48.7	56	80	330	NA	14	247
Volta	2.8	11.8	15.7	25	60	220	33	66	214
Eastern	3.3	6.8	5.3	30	30	100	37	19	31
Ashanti	9.6	9.3	12.4	80	50	82	49	22	33
Brong Ahafo	8.6	10.9	7.1	80	40	180	49	20	57
Northern	6.2	32.9	40.0	300	140	250	101	38	104
Upper East	2.6	7.1	10.8	100	100	160	62	37	114
Upper West	6.9	30.7	23.5	346	200	270	148	82	180
Total	6.2	12.9	14.1	90	85	180	44	33	93

Source: Authors based on GLSS 2006 and 2013.
[a]Figures are adjusted using sample weights.
[b]Include only the 80 ~ 90% of samples which report cultivated areas in acres or hectares.
[c]Sample size of farm households is fairly small in Greater Accra region.

Table 8 summarizes the share (%) of farm households owning tractors, by regions. These shares have remained low, at 0.2% in 2006, 0.7% in 2013, and 0.9% in 2017 compared to the shares of users (6.2%, 12.9%, and 14.1% respectively in Table 7, assuming most of those are tractors). This confirms that the significant growth of tractor use has occurred through rental.

Table 8. % of farm households owning tractors, by regions[a]

Regions	2006	2013	2017
Western	0.0	0.0	0.1
Central	0.0	0.0	0.0
Greater Accra[b]	0.0	5.7	1.1
Volta	0.5	0.0	1.5
Eastern	0.0	0.3	0.1
Ashanti	0.0	1.5	0.7
Brong Ahafo	0.4	0.5	0.3
Northern	1.2	1.6	2.4
Upper East	0.0	0.4	0.2
Upper West	0.2	1.6	5.7
Total	0.2	0.7	0.9

Source: Authors based on GLSS 2006 and 2013.
[a]Figures are adjusted using sample weights.
[b]Sample size of farm households is fairly small in Greater Accra region.

Table 9 presents the distributions of the expenditures on agricultural machinery rental in each year, by showing the quintile values. The figures suggest considerable variations across adopters, both in terms of overall expenditure, and expenditure per ha of cultivated areas. These findings further motivate our analyses on investigating the determinants of adoptions at intensive margins.

Table 9. Distributions of expenditures on agricultural machinery rental

Variables	Year	Quintile				
		Q1	Q2	Q3	Q4	Q5
expenditure on rental (nominal, cedi / year) at each quintile	2006	20	50	90	200	555
	2013	12	40	85	160	350
	2017	45	100	168	300	600
expenditure on rental per ha of cultivated area (nominal, cedi / ha, year) at each quintile	2006	9	20	43	92	346
	2013	6	15	33	62	113
	2017	14	49	92	148	247

Source: Authors based on GLSS 2006, 2013, and 2017.
[a]Figures are adjusted using sample weights.

Figure 1 illustrates the simple relationship between the probability of renting in agricultural machines, and farm size of the households. Consistent with the conventional wisdom, the adoption of agricultural machinery through rentals had been led by larger farms, and this pattern has become more pronounced in 2013 and 2017.

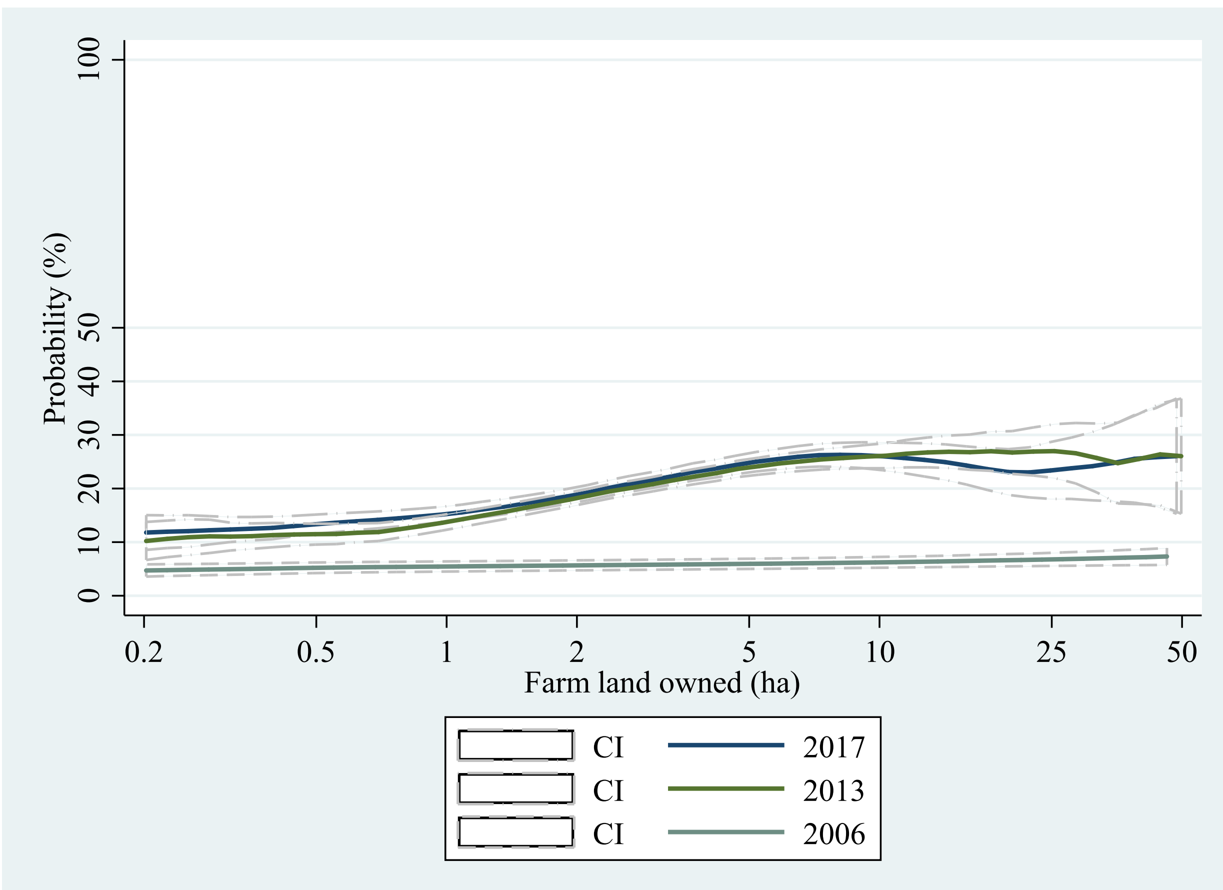

Figure 1. Farm size and probability of renting in agricultural machinery in Ghana
Source: Authors' estimations based on GLSS data.

Patterns observed from IFPRI-SARI data

While IFPRI-SARI data are purposively sampled, they provide further pictures of key characteristics of tractor use (Appendix B describes these patterns more in detail). First, rice is one of the crops for which mechanized tillage is commonly used. Since IFPRI-SARI data provide detailed information for tractor use on rice plots, our analyses on IFPRI-SARI data focus on rice.

Tractors are most commonly used for plowing, while its uses for harrowing, transportation and shelling are relatively minor (Table 19 and Table 20 in Appendix B). Furthermore, second plowing and harrowing by manual labor or animals are rare, and are only adopted when tractors are adopted. While it is unclear whether this pattern holds for the whole of Ghana, the pattern is consistent with the literature suggesting that primary tillage is among the first operations that become mechanized with tractors (Binswanger 1986).

Tractor owners also provide hiring services, typically in multiple districts, rather than their home districts alone, and about 1/6 of tractor owners in the sample also engage in seasonal migration to different rainfall zones, although, as is shown later, a significant share of service still takes place within home districts (Table 21 and Table 22 in Appendix B). These patterns suggest that the mobility of tractors might have somewhat improved by 2012 (period covered by IFPRI-SARI data). Furthermore, we have indicative evidence that access to tractors, both for potential owners, and smallholders hiring-in tractor services, had somewhat improved since 2006 (Table 23 through Table 25 in Appendix B). These indications of improvements in tractor market efficiency may partly suggest that tractor adoptions might have been increasingly determined by demand-side factors, including agroclimatic similarity and yield-potential, in more recent years.

4.3 Agroclimatic similarity

One of the variables of our interest is Agroclimatic Similarity with the locations of Plant Breeding Institutes (PBIs) (AS), which measures the similarity between the location of each farm household and the locations of PBIs in terms of soil, hydrological, and climate conditions. Conceptually, AS has been considered an important indicator of spillover potentials of agricultural technologies, particularly varietal technologies, which significantly affect the spatial variations in agricultural productivity (Alston, 2002; Evenson & Gollin, 2003; Walker & Alwang 2015; Lynam et al. 2016; Takeshima 2019).

An indicator of AS has been developed by Takeshima (2019), which is based on the sum of absolute differences in standardized values of each agroclimatic variables (between the locations of plant breeding and farm households), inspired by original methodologies developed by Bazzi et al. (2016).

One of the shortcomings of the original approach in Takeshima (2019) is that the indicator places equal weights to all agroclimatic variables of the same types (once standardized). Such approaches can be problematic when, for example, those agroclimatic variables are highly correlated.[6] Furthermore, the indicator is restrictive because it focuses on only one dimension of the agroclimatic conditions. In reality, however, the effects of agroclimatic conditions on yield potentials can be multi-dimensional, with different agroclimatic variables having different effects.

[6]For example, adding highly correlated agroecological variables can increase their relative importance in constructing agroclimatic similarity indicator, even though these variables contribute little additional information about the agroclimatic similarity beyond what is already capture by other agroclimatic variables.

We mitigate these problems by exploiting the Principal Components (PC) of agroclimatic variables. Specifically, we generate AS indices, $\sigma_{i.B}$, for household i with respect to specific PBIs, B as,

$$\sigma_{i.B,k} = -\left|\theta_i^k - \theta_B^k\right| \quad (1)$$

where θ_i^k and θ_B^k are the k-th PC of agroclimatic parameters θ in areas where household i and B are located, respectively. $\left|\theta_i^k - \theta_B^k\right|$ are absolute deviations. With the negative sign added in front, an increase in $\sigma_{i.B,k}$ indicates the increase in AS in terms of k-th PC. The similarity index for the household i with respect to k-th PC (σ_{ik}) is,

$$\sigma_{ik} = \max_B \sigma_{i,B,k}. \quad (2)$$

Thus, σ_{ik} is the AS with the most similar PBI for i, in terms of k-the PC of agroclimatic variables. Unlike in Takeshima (2019) which generates a single AS indicator, our approach captures AS in multiple-dimensions by using k indicator variables.

Since GLSS report only districts,[7] where sampled households reside, rather than lower administrative units, we construct σ_{ik} at the district level. However, in doing so, we incorporate the information of the intra-district distributions of agricultural land using Harvest Choice (2018), so that the AS index is calculated in ways that are more representative of farmland in each district. Note, IFPRI-SARI data provides more precise information of coordinates at village levels (Takeshima et al. 2018), and thus provides us variations in σ_{ik} even within districts.

Table 10 presents the results of Principal Component Analysis (PCA) applied to agroclimatic variables, expressed as the eigenvectors of the first 10 PCs. Predicted values of the PCs, θ_i^k and θ_B^k in equation (1), are obtained based on these eigenvectors, each of which is closely correlated with agroclimatic variables, but are perfectly uncorrelated across each other. Table 10 indicates that, the first PC accounts for 28 percent of all variations of agroclimatic variables, and the first 6 PCs account for 81 percent of all variations. Table 26 in Appendix C shows that correlations among σ_{ik} are fairly low, generally less than 0.2, except for a few cases.

[7]Between 2006 and 2017, number of districts in Ghana increased from 137 to 216, primarily by splitting existing districts into multiple new districts so that original district boundaries are retained.

Table 10. Principal component analysis of agroclimatic variables

Variables	Principal component (PC)									
	1	2	3	4	5	6	7	8	9	10
Rainfall	-.379	-.174	.010	.108	.223	-.005	.012	.579	.130	-.188
Wind	.294	.120	-.263	.340	-.282	-.069	.037	-.378	.473	-.174
Drainage (poor)	.314	.108	.398	.048	-.062	-.256	.192	.391	.411	-.290
Drainage (excessive)	-.107	-.232	.274	.397	-.166	.576	.293	-.093	.001	-.237
Sodicity of soil	.342	.093	-.006	.107	.487	.336	-.139	.180	.224	.080
Salinity of soil	.320	.178	-.097	.306	.379	.193	-.293	-.027	-.345	-.208
Coarse texture in the soil (%)	.283	-.207	-.256	-.162	-.139	.384	.513	.203	-.101	.292
Fine texture in the soil (%)	.204	.126	.497	.279	-.081	-.278	.239	-.006	-.496	.114
Organic content	-.318	-.097	.290	.396	.147	.046	-.133	-.203	.240	.523
pH of soil	.210	.288	.379	-.416	.039	.217	-.043	-.061	.145	.305
Elevation	-.270	.264	.284	-.330	-.074	.357	-.086	-.214	.028	-.401
Terrain ruggedness	-.216	.539	-.205	.137	.028	.033	.269	.051	-.206	-.134
Slope	-.233	.513	-.147	.102	.165	-.021	.369	.040	.201	.240
Euclidean distance to the nearest river	.000	.273	-.052	.187	-.613	.213	-.463	.438	-.052	.211
Share (%) of variations explained	28.3	42.1	54.0	65.0	73.8	81.0	86.3	90.4	93.2	95.3

Source: Authors.

Emerging mechanization adoptions in areas with higher agroclimatic similarity with plant breeding institutes

Figure 2 plots simple relations between agricultural machinery adoption rates and the AS index (first PC) in 2006, 2013 and 2017. As was described above, AS refers to the similarity of agroclimatic conditions between areas where smallholders are located and the areas where PBIs are located. The two variables are positively associated in general and this pattern has become more pronounced in 2013 and 2017 than in 2006.

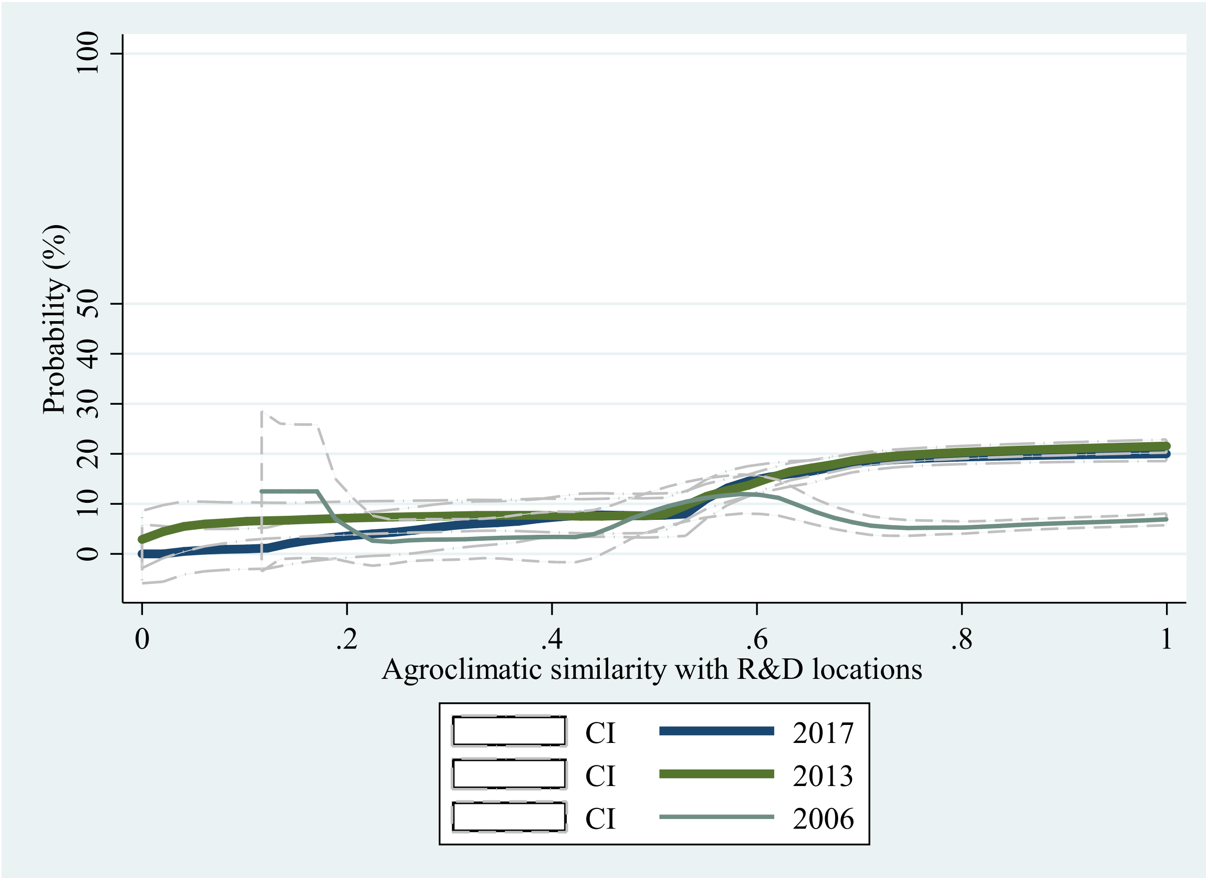

Figure 2. Agroclimatic similarity (with R&D locations) and probability of renting in agricultural machinery – based on the first principal component
Source: Authors' estimations based on GLSS data.

Despite the low correlations among σ_{ik} as mentioned above, many σ_{ik} have generally positive bilateral relations with the machinery adoptions, with data in 2013 and 2017 exhibiting clearer patterns (Figure 3 and Figure 4 for AS based on the second and the third PCs, and Figure 7 through Figure 9 in Appendix C for the fourth, fifth and the sixth PCs, respectively).

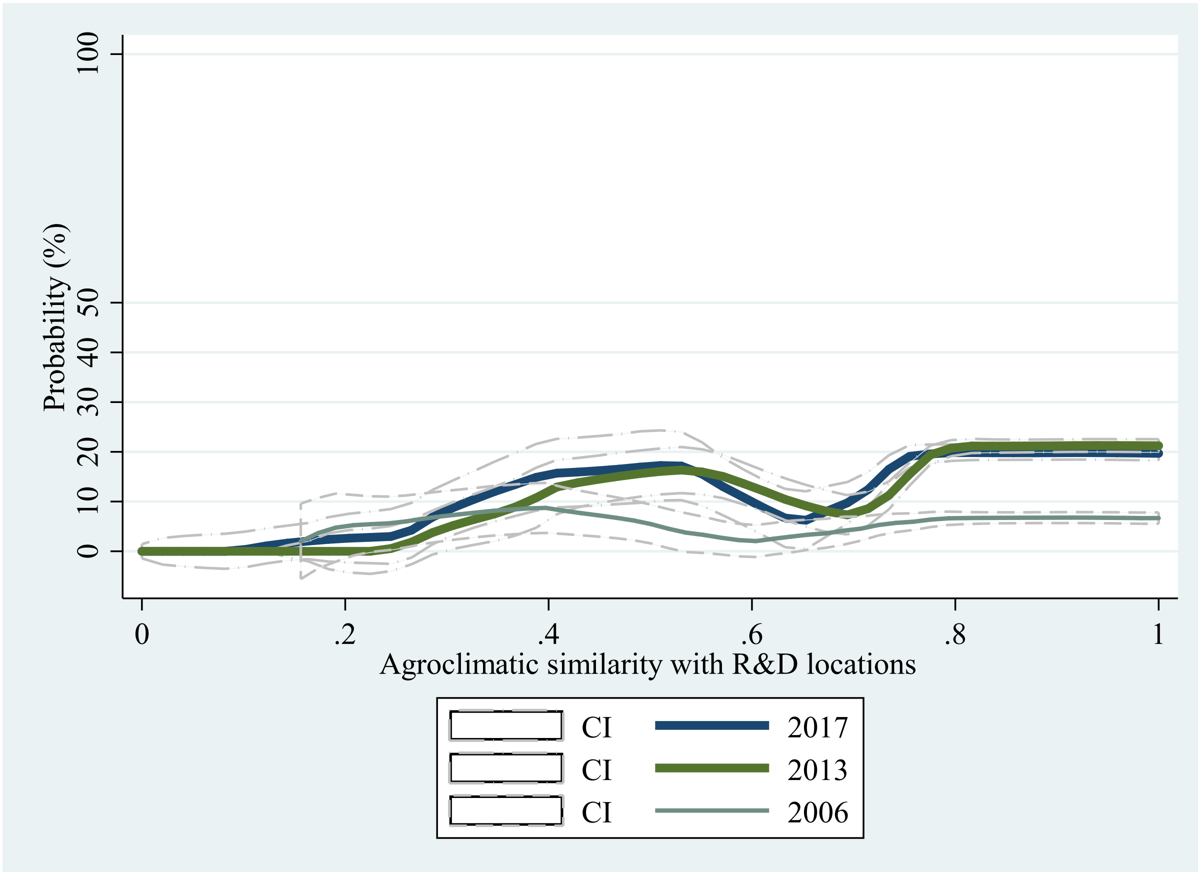

Figure 3. Agroclimatic similarity (with R&D locations) and probability of renting in agricultural machinery – based on the second principal component
Source: Authors' estimations based on GLSS data.

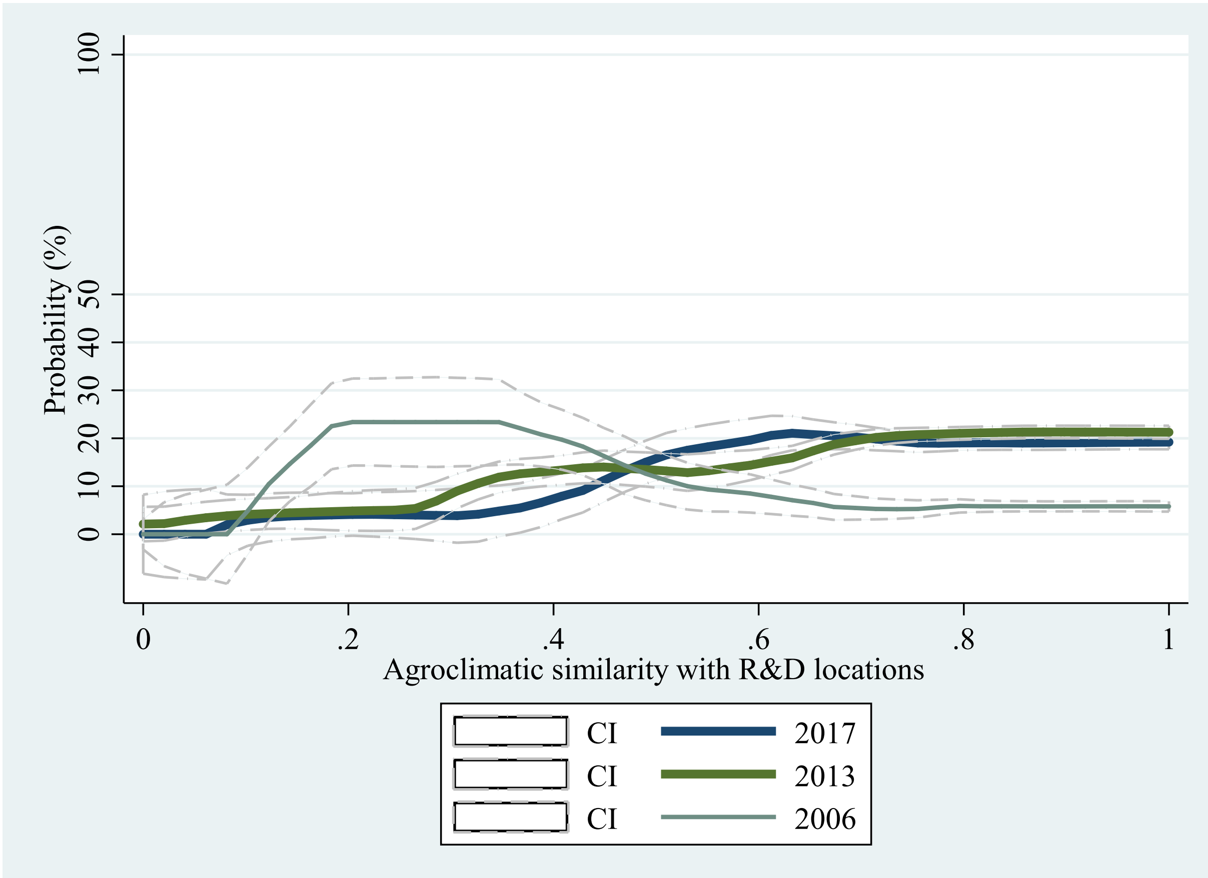

Figure 4. Agroclimatic similarity (with R&D locations) and probability of renting in agricultural machinery – based on the third principal component
Source: Authors' estimations based on GLSS data.

These patterns of rising correlations between machinery adoptions and AS between 2006 and 2013/2017 are also consistent with the indication of improving efficiency on supply-side described above. These patterns motivate our subsequent empirical analyses.

5 Empirical methods

Our main hypothesis is that higher yield, potentially induced by yield-enhancing biological technologies, induces farmers (especially smallholders) to rent in large agricultural machines like tractors, and use them more intensively per unit of land. Because PBIs have supplied most improved varieties in Ghana, we further hypothesize a positive causal effect of PBIs on machine rentals and its use intensity. The descriptive results show indicative patterns that are consistent with this hypothesis. We now explore the causal effects of PBIs and yields on mechanization adoptions.

To examine the effect of PBIs on machine adoption and its use-intensity, we estimate the following reduced-form regression:

$$y_i = \beta_0 + \beta_{\sigma k}\sigma_{ik} + \beta_A A_i + \beta_d d_i + \beta_z Z_i + e_i, \quad (3)$$

and structural equations of the effects of yield on machine adoption and its intensity,

$$y_i = \gamma_0 + \gamma_H H_i + \gamma_A A_i + \gamma_d d_i + \gamma_Z Z_i + u_i, \quad (4)$$

where y_i is a set of dependent variables (a binary variable indicating whether to rent in machines, and machine rental expense per ha of cultivated land) by household i.[8] A_i is the size of owned farm land. d_i is the Euclidean distance to the closest PBI. Z_i is a set of other key factors that may affect the demand for and supply of mechanization (described below). H_i is the yield measured as the aggregate production value of grain crops per hectare of land. Parameters β's and γ's are estimated coefficients. e_i and u_i are random error terms. σ_{ik} is agroclimatic similarity described above. Including multiple σ_{ik} as regressors can account for multi-dimensional aspects of AS. In the supplementary analyses with IFPRI-SARI data, y_i is tillage frequency (number of rounds of tillage conducted during the land preparation stage) on rice plots, for which IFPRI-SARI data contain detailed information.

Interpreting coefficients on agroclimatic similarity

The parameters of our interest are $\beta_{\sigma k}$ and γ_H. Statistically significantly positive signs of these parameters support our main hypotheses described above. Magnitudes of $\beta_{\sigma k}$ do not have straightforward economic interpretations, nor comparable among σ_{ik}. However, signs of $\beta_{\sigma k}$ indicate the effects of AS on dependent variables. If statistically significant signs of $\beta_{\sigma k}$ are in the same directions among all k, they indicate that the observed effects of AS hold across multiple-dimensions of agroclimatic conditions. We show in the results section that, $\beta_{\sigma k}$ are either statistically significantly positive (for some k) or statistically insignificant, but not statistically significantly negative.

It is common in the empirical analyses to include PCs that account for 70 – 90 percent of variations in the original variables. In our primary specification, we use σ_{ik} with $k = 1, \dots, 6$, because, as was shown, the PCA suggest that the first 6 PCs account for about 80 percent of all variations in our 14 agroclimatic variables.

Standard errors

Since σ_{ik} are based on PCs which are generated variables, the variance of the second-step estimates tends to be inflated by the errors embedded in PCs (Pagan 1984). We therefore adjust the standard errors through paired bootstrap (Efron 1979; Freedman 1981). As is stated in MacKinnon (2009 p193), paired bootstrap also provides standard errors that are robust against the presence of an unknown form of heteroskedasticity in idiosyncratic error terms.

Other control variables

Variables Z_i largely consist of (a) raw agroclimatic variables θ_i^k; (b) household demographics and wealth indicators; (c) access to markets and infrastructure; (d) other agricultural inputs.

Raw agroclimatic variables include annual rainfall, annual average of wind-speed at 10 meters above ground, various soil qualities (shares of soils with poor drainage and excess drainage, sodicity, salinity, share of coarse, fine texture, organic content, and acidity), elevation, terrain ruggedness, slope and the Euclidean distance to the nearest river. Many of these variables

[8] Note that, for use-intensity, we are interested in the rental spending ***per unit of farm area***.

are found to be important factors that affect agricultural productivity in general and adaptability of agricultural machines in West Africa (Takeshima 2019; Takeshima et al. 2018).

Household demographics include age, gender and formal education level of household head, and household size. Wealth indicators include the values of livestock, non-productive assets, agricultural capital, and non-farm enterprise assets owned by the household. A dummy variable indicating the ownership of tractors is also included, as own tractors are expected to have direct effects on the uses of rented machines, not simply the indirect liquidity effects.

Access to markets and infrastructure is proxied by the distances to the nearest road / public transportation facilities, the nearest market, and the nearest extension office.

Other agricultural inputs include an indicator of the cost of hired labor (measured as the wage), the sample shares of farm households using irrigation, and chemical fertilizer within the same EAs, the real value of agricultural land in the area. The sample shares of these inputs users are included as they are more likely to be exogenous to households' machine use, but still capture important spatial variations in the local access to these inputs.

We also include the dummy variable indicating the presence of tractor owners among samples in the same EA, which can partly control for the access to custom-hiring service, given the limited mobility of tractors in SSA mentioned above. Lastly, we also include the Herfindahl (Simpson) index of land fragmentation, based on all plots owned by the household. It is calculated as $1 - \Sigma_i a_j^2$ with a_j^2 being the area share of plot j. The index ranges between one (most fragmentation) and zero (least fragmentation).

Lastly, dummy variables indicating sectors (rural / urban), years, 10 regions in Ghana are included.

Analyses on IFPRI-SARI data use alternative variables where some variables are unavailable. Specifically, distance to the nearest 20k population town (Harvest Choice 2018) and a dummy variable indicating whether the government is the primary source of extension, are used in place of aforementioned variables for access to markets and extension offices. EA sample share of fertilizer users is replaced with the local price of fertilizer, the land-value variable is replaced by an indicator of household perceptions of land tenure security. Lastly, since IFPRI-SARI data include only rural farm households, and asset ownership of non-farm enterprises are not reported, these and sector dummy (rural/urban) are thus excluded.

Estimation methods

Equations (3) and (4) estimate the determinants of agricultural machinery adoption, at both extensive margins and intensive margins. Model (3) is a reduced form. Because of the truncated nature of the machine adoption intensity, we apply Cragg's double-hurdle (DH) model. To mitigate the problem of failed convergence in estimates often associated with conventional DH model, we apply generalized double-hurdle model proposed by Yen (1993). For (3), we also estimate the linear probability model (LPM) for robustness purposes. For (4) on tillage frequency in IFPRI-SARI data, count variable methods like Ordered Probit are also used.

Model (4) is structural, and H_i may be endogenous to machinery adoptions. To deal with this endogeneity problem, we estimate (4) using instrumental variable (IV) methods. Because plant-breeding research in countries like Ghana has focused largely on yield-enhancement, AS indicators can naturally serve as good IVs (a similar approach has been used in other studies like Takeshima & Liu 2018). The literature also shows the consistency of IV least-square (LS) methods when PCs are used as IVs, like ours (Kloek & Mennes 1960; Amemiya 1966), which has been increasingly applied in empirical work (Stock & Watson 2002; Bai & Ng 2010;

Kapetanios & Marcellino 2010; Emran & Hou 2013).[9] In contrast, literature is still thin on the consistency of using PC-based IVs for IV-probit or IV-truncated regressions.[10] Therefore, for (4), the adoption at extensive margins is estimated through IV-LPM (i.e., two-stage least square (2SLS)), while the adoption at intensive margins is estimated through Heckman's sample-selection method (Heckman 1979) combined with 2SLS for the second-stage.[11]

Supplementary estimation with IFPRI-SARI data – locations of service provisions

Even if we find significantly positive $\beta\sigma k$ and γ_H, it may be simply because high AS and yield-potentials are somehow correlated with unobserved factors that affect efficiency of tractor hiring service. This possibility is important particularly in the case of tractor hiring services for which market imperfections can arise due to many unique constraints, such as indivisibility of tractors.

Unique information about tractor service provisions in IFPRI-SARI data can provide indicative evidence to partly clarify this question. Specifically, we provide some insights by examining the determinants of service provision locations. We estimate

$$s_{ii} = \delta_0 + \delta_{\sigma k}\sigma_{ik} + \delta_d d_i + \delta_D D_{ii} + \delta_Z Z_i + c_i + v_{ij}, \quad (5)$$

in which $s_{ij} = 1$ if a tractor owner i used tractors in destination-district j, while σ_{jk}, d_j are AS and distance to the nearest PBIs for destination-district j, respectively c_i is unobserved fixed-effects of tractor owner i, and v_{ij} is the idiosyncratic error. D_{ij} is the Euclidean distances between tractor owner i's district and destination-district j. Parameters δ's are estimated coefficients. Here, variables Z_j include other factors that can affect the demand and supply of tractor hiring services in destination-district j, such as raw agroclimatic conditions θ, district size, population density, the presence of tractor owners (proxied by whether and how many GLSS samples for the particular districts had tractor owners in 2013), crop area per capita inferred from Harvest Choice (2018) and district-level agricultural population (MOFA 2016), and district-average night light intensity (NOAA 2018) that proxies the level of economic development. Z_j also includes district j's level of isolation (measured as j's average distance to all the other districts). Regional dummy variable is also included to account for region-specific effects. Further, three-dummy variables are also included; whether j is a "home-district" ($i = j$), whether j is one of the 8 districts where tractor owners were interviewed in IFPRI-SARI data ("sample-district"), and whether one of the major 4 sample-districts ("major-sample-districts").[12]

In equation (5), the effects of all the characteristics of tractor owner i are netted out by c_i. Aforementioned potential correlations between AS or yields, and unobserved factors affecting supply-side market efficiency, can be partly captured by their correlations with c_i. For example, a disproportionate share of tractor service providers that are more mobile or efficient in serving outside districts (and thus high c_i) may be located in or near districts with high σ_{jk} and yields,

[9]PC-based IVs are also used to reduce the number of potential IVs, which is one of the practical approaches to maintain the validity by avoiding overidentification (Carrasco 2012; Bontempi & Mammi 2014).
[10]IV-truncated regression, when IVs are conventional non-PC variables, have been used in the literature (eg., Ricker-Gilbert et al. 2011).
[11]IV-Heckman has been used in past studies (eg., Bellemare & Barrett 2006; Takeshima & Winter-Nelson 2012).
[12]The 8 sample-districts are Ejura-Sekyedumase, Techiman, Kintampo North, Yendi, Gushiegu, Kassena-Nankana East, Bawku, Sissala East), while 4 major-sample districts, where most interviewed tractor owners are located, are Ejura-Sekyedumase, Yendi, Gushiegu, Sissala East.

which could cause spurious relations between σ_{jk} or yield and machine rental. Positive $\delta_{\sigma k}$ (after c_i is controlled for) would indicate that, the effects of σ_{jk} on tractor adoptions in (3) may hold even after controlling for some correlations between σ_{jk} and unobserved supply-side constraints, and offer stronger evidence of demand-side linkages.

In equation (5), because all destination-district characteristic variables including σ_{jk} are measured at district-level, they cannot be separately identified from destination-district fixed effects. (5) is identifiable with the assumption that υ_{ij} contains no destination-district fixed effects correlated with regressors including σ_{jk}. This assumption may be reasonable given that in 2012 and early 2013 when the survey was conducted, Ghana's agricultural policies were still largely resourced and implemented by the Central government rather than district governments, compared to later years (Resnick 2018).

6 Results

6.1 Results based on GLSS

Table 11 summarize the estimated effects of 6 PCs of agroclimatic similarity on agricultural equipment rental at both extensive and intensive margins, with and without year interaction dummies, as well as using whole sample and subset of samples focusing on those owning less than 10 ha of land. Similarly, Table 12 summarizes the estimated effects of yields on agricultural equipment at both margins, with similar breakdown by samples.

Table 11. Effects of agroclimatic similarity with PBIs on machine rental

Variables	Extensive margins: Whether to rent in agricultural machines		Extensive margins: Whether to rent in agricultural machines		Intensive margins: Machine expenditure per ha	
	Linear probability model		Probit		Truncated regression (λ = 0.5)	
	Coef.	Std.err[a]	Coef.	Std.err[a]	Coef.	Std.err[a]
All sample						
Ag similarity (PC 1)	-.022	(.020)	.009	(.038)	.000	(.030)
Ag similarity (PC 2)	-.016	(.013)	-.021	(.029)	.019	(.048)
Ag similarity (PC 3)	**.042****	(.021)	**.070****	(.036)	**.074****	(.029)
Ag similarity (PC 4)	-.033	(.023)	-.038	(.036)	-.057	(.054)
Ag similarity (PC 5)	.028	(.020)	**.052***	(.032)	-.003	(.036)
Ag similarity (PC 6)	-.008	(.019)	-.014	(.034)	-.018	(.033)
Ag similarity (PC 1)	-.032	(.020)	-.019	(.039)	-.006	(.031)
Ag similarity (PC 2)	-.016	(.013)	-.021	(.029)	.015	(.052)
Ag similarity (PC 3)	**.055*****	(.021)	**.077****	(.036)	**.074****	(.033)
Ag similarity (PC 4)	-.034	(.023)	-.036	(.036)	-.060	(.054)
Ag similarity (PC 5)	.029	(.020)	**.065****	(.032)	-.003	(.036)
Ag similarity (PC 6)	-.006	(.019)	.014	(.034)	-.024	(.034)
Ag similarity (PC 1) *year 2013/2017	**.040*****	(.012)	**.086****	(.034)	-.011	(.016)
Ag similarity (PC 2) *year 2013/2017	.008	(.009)	.008	(.025)	-.021	(.027)
Ag similarity (PC 3) *year 2013/2017	**.055*****	(.016)	**.117*****	(.036)	.009	(.016)
Ag similarity (PC 4) *year 2013/2017	.004	(.012)	-.010	(.030)	.012	(.020)
Ag similarity (PC 5) *year 2013/2017	-.005	(.014)	-.033	(.033)	.016	(.027)
Ag similarity (PC 6) *year 2013/2017	.004	(.012)	.002	(.032)	.042	(.033)
Smallholders (< 10 ha of own land)						
Ag similarity (PC 1)	-.017	(.020)	.015	(.039)	-.006	(.031)
Ag similarity (PC 2)	.015	(.013)	-.018	(.029)	.010	(.049)
Ag similarity (PC 3)	**.043****	(.022)	**.074****	(.037)	**.078*****	(.029)
Ag similarity (PC 4)	-.030	(.024)	-.033	(.036)	-.077	(.053)
Ag similarity (PC 5)	.025	(.020)	.047	(.032)	.000	(.037)
Ag similarity (PC 6)	-.010	(.019)	-.016	(.035)	-.020	(.033)
Ag similarity (PC 1)	-.027	(.021)	-.011	(.040)	-.013	(.032)
Ag similarity (PC 2)	-.014	(.013)	-.017	(.029)	.005	(.052)
Ag similarity (PC 3)	**.046****	(.021)	**.080****	(.036)	**.079****	(.033)
Ag similarity (PC 4)	-.032	(.024)	-.030	(.036)	-.084	(.053)
Ag similarity (PC 5)	.026	(.020)	**.057***	(.032)	.001	(.036)
Ag similarity (PC 6)	-.007	(.019)	-.017	(.035)	-.029	(.034)
Ag similarity (PC 1) *year 2013/2017	**.036*****	(.012)	**.079****	(.034)	-.011	(.016)
Ag similarity (PC 2) *year 2013/2017	.008	(.009)	.009	(.026)	-.023	(.028)
Ag similarity (PC 3) *year 2013/2017	**.057*****	(.017)	**.122*****	(.031)	.012	(.017)
Ag similarity (PC 4) *year 2013/2017	.002	(.012)	-.018	(.031)	.020	(.021)
Ag similarity (PC 5) *year 2013/2017	-.001	(.014)	-.022	(.033)	.017	(.028)
Ag similarity (PC 6) *year 2013/2017	.006	(.012)	.007	(.033)	.044	(.033)

Source: Authors' estimations. Asterisks indicate the statistical significance *** 1% ** 5% * 10%.

Table 12. Effects of yield on machine rental at extensive and intensive-margins

Variables	Extensive margins: Whether to rent in agricultural machines		Intensive margins: Machine expenditure per ha		Intensive margins: Machine expenditure per ha	
	IV linear probability model		Exogenous Heckman's method		Endogenous Heckman's method	
	Coef.	Std.err[a]	Coef.	Std.err[a]	Coef.	Std.err[a]
All sample						
ln (Yield)	1.376*	(.748)	.202***	(.033)	.432*	(.253)
ln (Yield)	1.105***	(.354)	.112	(.093)	.584*	(.320)
ln (Yield) * year 2013/2017	1.226	(.966)	.198	(.178)	-.365	(.708)
Smallholders (< 10 ha of own land)						
ln (Yield)	1.393*	(.793)	.202***	(.034)	.461*	(.258)
ln (Yield)	1.097***	(.351)	.129	(.095)	.585*	(.318)
ln (Yield) * year 2013/2017	1.166	(.949)	.166	(.185)	-.313	(.699)

Source: Authors' estimations. Asterisks indicate the statistical significance *** 1% ** 5% * 10%

Some AS variables are statistically significantly positive while none are statistically significantly negative (Table 11). In other words, AS is generally positively associated with the probability of adopting machines through rental, and rental spending upon renting, even when considering the multi-dimensional nature of the agroclimatic conditions. Furthermore, some interaction terms with year dummy variables (2013 and 2017 compared to 2006) are statistically significantly positive, while none are significantly negatively. The positive effects of AS on agricultural equipment rental have thus been strengthened in 2013 and 2017 compared to 2006. This effect is clearer for agricultural equipment rental at extensive margins, although less clear for intensive margins. Similarly, yield has statistically significantly positive effects on agricultural equipment rental at both extensive and intensive margins (Table 12). These results hold both for all sample and for sub-sample. Here, none of the year-interaction terms is significant, suggesting that, even in 2006, machine rental was significantly induced once high-yielding production was possible.

The greater AS is in fact associated with higher yield (Table 27 in Appendix D), consistent with the literature on the role of public-sector plant breeding and spillover patterns.

Results so far are consistent with our hypotheses that the emergence of higher-yielding production system, partly induced by public-sector plant breeding, has raised the demand for and adoption of rented agricultural equipment among Ghanaian farmers, majority of whom are still relatively small. Furthermore, this linkage has become stronger since 2006, partly through improved efficiency on the supply-side.

Other coefficients

Table 13 and Table 14 present the results on other coefficients, corresponding to the main results in Table 11 and Table 12. Signs of other coefficients are intuitive. The greater total size of farmland generally induces machine adoption, consistent with the well-known complementarity between machine and land, while intensity of use *per area* is higher on smaller plots. Adoption probability is higher in areas closer to road / public transportation, as well as extension offices, which generally stimulate more intensive use of modern production methods. Households with younger heads are more likely to adopt, potentially because younger farmers may be more willing to adopt modern mechanical equipment. Adoptions are also induced by greater non-productive assets that provide more liquidity for purchasing modern inputs and services, and non-farm enterprise assets that either allows processing of harvests, or raises opportunity costs of family labors for farming. Similarly, higher farm wages for hired labor may induce adoptions of machines as substitutes at intensive margins. The existence of tractor owners among the sample within the same EAs is positively associated with machine adoption, consistent with earlier studies on SSA indicating the generally limited mobility of tractors beyond local areas (Takeshima et al. 2015; Takeshima et al. 2018). The greater use of irrigation and chemical fertilizer in the local area, which can also vary spatially, is also positively associated with machine adoptions, consistent with the hypotheses about the complementarity between yield-enhancing inputs and agricultural machines. Not surprisingly, having own tractors significantly discourage renting-in of equipment (which are also mostly tractors). Lastly, adoption is higher if owned farmland plots are more fragmented, possibly because more fragmentation may mean a higher chance that farmers have at least some plots that are more easily accessible by tractors (this contrasts with Asia where all plots are relatively accessible (eg., Deininger et al. 2017)).

Table 13. Determinants of agricultural machine rental and rental intensity (Generalized Double-Hurdle Model)

Variables	Extensive margins: Whether to rent in agricultural machines		Extensive margins: Whether to rent in agricultural machines		Intensive margins: Machine expenditure per ha	
	Linear probability model		Probit		Truncated regression (λ = 0.5)	
	Coef.	Std.err[a]	Coef.	Std.err[a]	Coef.	Std.err[a]
Ag similarity (PC 1)	-.032	(.020)	-.019	(.039)	-.006	(.031)
Ag similarity (PC 2)	-.016	(.013)	-.021	(.029)	.015	(.052)
Ag similarity (PC 3)	**.055*** **	(.021)	**.077** **	(.036)	**.074** **	(.033)
Ag similarity (PC 4)	-.034	(.023)	-.036	(.036)	-.060	(.054)
Ag similarity (PC 5)	.029	(.020)	**.065** **	(.032)	-.003	(.036)
Ag similarity (PC 6)	-.006	(.019)	.014	(.034)	-.024	(.034)
Ag similarity (PC 1) * year2013/2017	**.040*** **	(.012)	**.086** **	(.034)	-.011	(.016)
Ag similarity (PC 2) * year2013/2017	.008	(.009)	.008	(.025)	-.021	(.027)
Ag similarity (PC 3) * year2013/2017	**.055*** **	(.016)	**.117*** **	(.031)	.009	(.016)
Ag similarity (PC 4) * year2013/2017	.004	(.012)	-.010	(.030)	.012	(.020)
Ag similarity (PC 5) * year2013/2017	-.005	(.014)	-.033	(.033)	.016	(.027)
Ag similarity (PC 6) * year2013/2017	.004	(.012)	.002	(.032)	.042	(.033)
Farmland owned (ha, natural log)	.061***	(.015)	.090***	(.023)	-.136***	(.022)
Distance to road / public transportation	-.020	(.020)	-.044	(.037)	-.060**	(.030)
Distance to market	.017	(.021)	.030	(.035)	.010	(.029)
Distance to extension office	-.042**	(.021)	-.078**	(.034)	.012	(.030)
Distance to the nearest plant breeding institute	.020	(.023)	.028	(.036)	-.016	(.034)
Household size	.018*	(.011)	.029*	(.017)	.000	(.017)
Age of head	-.032***	(.009)	-.058***	(.016)	-.033*	(.019)
Gender of head (female = 1)	.010	(.009)	.019	(.017)	.016	(.018)
Education of head (years)	-.002	(.011)	.005	(.019)	.045**	(.019)
Livestock (value, natural log)	.017	(.013)	.037*	(.021)	.010	(.022)
Non-productive assets (value, natural log)	.046***	(.012)	.085***	(.022)	.043**	(.021)
Agricultural capital (value, natural log)	-.024	(.015)	-.036	(.024)	.024	(.023)
Non-farm enterprise asset (value, natural log)	.014	(.011)	.030*	(.016)	-.031*	(.018)
Farm wage (natural log)	.030	(.027)	.053	(.043)	.066*	(.039)
Land value per hectare (natural log)	-.042**	(.019)	-.062*	(.034)	-.078**	(.033)
EA sample share of irrigators	.032*	(.018)	.046**	(.019)	.076	(.048)
EA sample share of fertilizer users	.129***	(.022)	.196***	(.033)	.080***	(.029)
Land fragmentation index	.037***	(.013)	.056**	(.022)	.013	(.023)
Owning tractors (yes = 1)	-.659***	(.129)	-.863***	(.186)	-.117	(.223)
EA sample share of tractor owners	.050*	(.027)	.048*	(.029)		
Agroclimatic variables (6 PCs)	Included		Included		Included	
Region dummies	Included		Included		Included	
Sector dummy (rural / urban)	Included		Included		Included	
Year dummies	Included		Included		Included	
Intercept	Included		Included		Included	
Number of observations	16,517		16,517		2,424	
p-value (H_0: variables jointly insignificant)	.000		.000		.000	

Source: Authors' estimations. Asterisks indicate the statistical significance *** 1% ** 5% * 10%
[a]Standard errors are based on heteroskedasticity-robust paired bootstrap (Efron 1979; Freedman 1981).

Table 14. Effects of high-yielding production systems on agricultural machine rental and rental intensity

Variables	Extensive margins: Whether to rent in agricultural machines		Intensive margins: Machine expenditure per ha	
	IV linear probability model		Endogenous Heckman's method	
	Coef.	Std.err[a]	Coef.	Std.err[a]
Yield (natural log)	1.097***	(.351)	.583*	(.320)
Yield (natural log) * year2013/2017	1.166	(.949)	-.365	(.708)
Farmland owned (ha, natural log)	.110***	(.022)	-.257***	(.040)
Distance to road / public transportation	.010	(.020)	.009	(.034)
Distance to market	-.008	(.020)	-.068**	(.037)
Distance to extension office	-.035*	(.018)	.075*	(.045)
Distance to the nearest plant breeding institute	.033	(.020)	-.041	(.029)
Household size	.017	(.017)	-.021	(.028)
Age of head	.033	(.021)	.040	(.033)
Gender of head (female = 1)	.089***	(.025)	-.028	(.025)
Education of head (years)	-.028	(.020)	-.005	(.030)
Livestock (value, natural log)	-.050**	(.023)	-.086**	(.034)
Non-productive assets (value, natural log)	-.064**	(.030)	-.062	(.046)
Agricultural capital (value, natural log)	-.048**	(.019)	.023	(.029)
Non-farm enterprise asset (value, natural log)	.008	(.016)	-.104***	(.027)
Farm wage (natural log)	.098***	(.026)	-.034	(.033)
Land value per hectare (natural log)	-.066***	(.020)	-.050	(.042)
EA sample share of irrigators	-.043	(.027)	-.146**	(.060)
EA sample share of fertilizer users	-.064	(.044)	-.210	(.086)
Land fragmentation index	-.013	(.020)	-.038	(.037)
Owning tractors (yes = 1)	-1.009***	(.166)	-.122***	(.037)
Inverse Mills Ratio			-.644***	(.200)
EA sample share of tractor owners	.004	(.022)		
Agroclimatic variables (6 PCs)	Included		Included	
Region dummies	Included		Included	
Sector dummy (rural / urban)	Included		Included	
Year dummies	Included		Included	
Intercept	Included		Included	
Number of observations	12,164		2,000	
p-value (H_0: variables jointly insignificant)	.000		.000	
p-value (H_0: yield is exogenous)	.000		.028	
p-value (H_0: not overidentified)	.407		.559	

Source: Authors' estimations. Asterisks indicate the statistical significance *** 1% ** 5% * 10%

Signs of other coefficients in structural models (Table 14) can differ from those in Table 13 if their indirect contributions to machine adoptions through yield are already captured by the direct effect of yield variable. Once the direct effect of yield is controlled for, the signs of various asset variables, as well as irrigation, turn negative. These possibly reflect that, once their indirect effects through yield are separated out, these variables may serve as substitutes for machines.

6.2 Results from IFPRI-SARI data

Results based on IFPRI-SARI data further confirm the hypotheses partly supported by GLSS data. Table 15 shows the effects AS on tractor use intensity (frequency of harrowing and plowing) on rice plots for farmers with less than 20 ha and 10 ha of land, respectively. Results are shown for OLS and Ordered Probit. For all specifications, tractor use intensity is significantly positively affected by various PCs of agroclimatic similarity (PC2 and PC5). Table 15 is consistent with our hypotheses that tractor use intensity is positively affected by higher AS.

Table 15. Determinants of tractor use intensity (frequency of harrowing, tillage) on rice plots[a]

Variables	owned farm size < 20ha				owned farm size < 10ha			
	OLS		Ordered probit		OLS		Ordered probit	
	Coef.	Std. err	Coef.	Std. err	Coef.	Std. err	Coef.	Std. err
Ag similarity (PC 1)	.016	(.054)	.034	(.123)	-.053	(.069)	-.165	(.158)
Ag similarity (PC 2)	.063*	(.036)	.136*	(.080)	.097*	(.052)	.230*	(.123)
Ag similarity (PC 3)	-.021	(.030)	-.058	(.066)	-.031	(.048)	-.094	(.103)
Ag similarity (PC 4)	-.058	(.072)	-.134	(.158)	-.040	(.087)	-.112	(.192)
Ag similarity (PC 5)	.069*	(.037)	.142*	(.080)	.083**	(.041)	.213**	(.091)
Ag similarity (PC 6)	.020	(.079)	.053	(.177)	-.046	(.085)	-.151	(.198)
Farmland owned (ha, natural log)	.175***	(.039)	.391***	(.085)	.169***	(.052)	.394***	(.108)
Distance to the nearest 20k population town	.006	(.043)	.026	(.099)	.065	(.054)	.191	(.122)
Government extension as primary source	.025	(.029)	.059	(.059)	.038	(.038)	.082	(.075)
Distance to the nearest PBI	.168*	(.099)	.409	(.237)	-.002	(.160)	-.036	(.374)
Household size	.007	(.023)	.016	(.050)	-.047	(.031)	-.099	(.068)
Age of head	-.036	(.029)	-.096	(.067)	-.013	(.032)	-.047	(.075)
Gender of head (female = 1)	.039	(.041)	.090	(.092)	.027	(.048)	.069	(.108)
Education of head (years)	.019	(.035)	.047	(.077)	.054	(.042)	.120	(.088)
Livestock (value, natural log)	-.026	(.042)	-.041	(.085)	-.016	(.054)	-.010	(.108)
Non-productive assets (value, natural log)	.227	(.228)	.459	(.501)	.271	(.739)	.328	(1.471)
Agricultural capital (value, natural log)	-.232	(.249)	-.454	(.547)	-.274	(.758)	-.312	(1.507)
Farm wage (natural log)	.021	(.045)	.052	(.090)	.017	(.068)	.062	(.144)
Land tenure security	.024	(.038)	.047	(.079)	.028	(.059)	.053	(.111)
Village sample share of irrigators	.054	(.039)	.120	(.080)	.087	(.057)	.181	(.115)
Price of fertilizer (value, natural log)	-.006	(.026)	-.007	(.064)	-.008	(.036)	-.013	(.081)
Village sample share of tractor owners	-.047	(.045)	-.111	(.092)	-.021	(.053)	-.043	(.095)
Land fragmentation index	-.055*	(.029)	-.133**	(.065)	-.064*	(.034)	-.178**	(.079)
Own tractor (yes = 1)	.101	(.187)	.186	(.364)	-.138	(.613)	-.482	(1.200)
Agroclimatic variables (6 PCs)	Included		Included		Included		Included	
Region dummies	Included		Included		Included		Included	
Intercept	Included		Included		Included		Included	
Number of observations	385		385		252		252	
R^2 (Psueod-R^2)	.390		.246		.365		.234	
p-value (H0: variables jointly insignificant)	.000		.000		.000		.000	

Source: Authors' estimations. Asterisks indicate the statistical significance *** 1% ** 5% * 10% †15%
[a]Standard errors are based on heteroskedasticity-robust paired bootstrap (Efron 1979; Freedman 1981).

Furthermore, Table 16 provides additional evidence on the mechanism of the observed effects of agroclimatic similarity with PBIs. Specifically, Table 16 provides some evidence that the positive effects occur through the effects on yield. In addition, Table 28 in Appendix D shows that rice yield is in fact generally positively affected by AS.

Table 16. Effects of rice yield on tractor use intensity (frequency of harrowing, tillage) on rice plots – two-stage least square

Variables	owned farm size < 20ha		owned farm size < 10ha	
	Coef.	Std.err[a]	Coef.	Std.err[a]
Rice yield	.424*	(.231)	.569*	(.298)
Farmland owned (ha, natural log)	.172***	(.033)	.209***	(.046)
Distance to the nearest 20k population town	.015	(.058)	.119	(.094)
Government extension as primary source (yes = 1)	-.007	(.033)	-.051	(.051)
Distance to the nearest plant breeding institute	-.038	(.168)	-.226	(.246)
Household size	-.016	(.032)	-.124**	(.060)
Age of head	-.038	(.036)	-.022	(.044)
Gender of head (female = 1)	.111**	(.049)	.103**	(.052)
Education of head (years)	.016	(.029)	-.007	(.055)
Livestock (value, natural log)	-.003	(.038)	-.009	(.047)
Non-productive assets (value, natural log)	-.188	(.324)	-.211	(.772)
Agricultural capital (value, natural log)	.189	(.341)	.213	(.808)
Farm wage (natural log)	-.008	(.048)	-.008	(.065)
Land tenure security	.058	(.046)	.086	(.079)
Village sample share of irrigators	-.034	(.070)	-.036	(.088)
Price of fertilizer (value, natural log)	-.003	(.032)	-.005	(.045)
Village sample share of tractor owners	-.012	(.051)	.019	(.074)
Land fragmentation index	-.066**	(.026)	-.090***	(.034)
Own tractor (yes = 1)	-.138	(.263)	-.358	(.725)
Agroclimatic variables (6 PCs)	Included		Included	
Region dummies	Included		Included	
Intercept	Included		Included	
Number of observations	385		252	
p-value (H_0: variables jointly insignificant)	.000		.000	
p-value (H_0: rice yield is exogenous)	.056		.040	
p-value (H_0: not over-identified)	.371		.723	
p-value (H_0: under-identified)	.119		.531	

Source: Authors' estimations. Asterisks indicate the statistical significance *** 1% ** 5% * 10% †15%
[a]Standard errors are based on heteroskedasticity-robust paired bootstrap (Efron 1979; Freedman 1981).

Supplementary results from IFPRI-SARI data – location of service provisions by tractor owners

Lastly, Table 17 shows the estimated results of the determinants of service locations by tractor owners (equation (5)). Equation (5) is estimated using 70,720 (= 170 districts times 416 tractor owners) observations, using the responses in IFPRI-SARI survey where tractor owners are asked to identify up to 5 locations that they used tractors including through hiring services.
The results suggest that, conditional on the fixed effects of tractor owners, they are more likely to provide services in districts that have higher agroclimatic similarity with plant-breeding institutions. This holds even after controlling for other factors, including the distance to these destination districts from tractor owners' districts, distance to the nearest PBIs from these destination districts, and other characteristics of these destination districts. These effects also hold if we exclude the own-districts, and focus exclusively on service provisions in out-side districts (2nd results). Consistent with earlier studies in West Africa (eg., Takeshima et al. 2015), tractor mobility is somewhat limited as indicated by significantly negative coefficients on the distance to the destination district from the home district. However, significantly positive coefficients suggest that tractor owners may partly overcome the mobility constraints and still

travel to distant districts if those districts have sufficiently high agroclimatic similarity with PBIs.

Table 17. Determinants of locations of tractor hiring service provisions: Effects of (effects of one-standard deviation change)

Variables	Conditional logit		Fixed effect linear probability model	
	Coef.	Std.err[a]	Coef.	Std.err[a]
Ag similarity (PC 1) of *destination district*	.098	(.246)	.007	(.005)
Ag similarity (PC 2) of *destination district*	-.055	(.142)	.008*	(.004)
Ag similarity (PC 3) of *destination district*	.024	(.091)	-.005	(.005)
Ag similarity (PC 4) of *destination district*	.082	(.089)	-.006	(.004)
Ag similarity (PC 5) of *destination district*	.231**	(.099)	.008*	(.004)
Ag similarity (PC 6) of *destination district*	-.071	(.072)	-.001	(.003)
Distance to the *destination district*	-1.513***	(.189)	-.060***	(.016)
Distance to the nearest PBIs from *destination district*	-.411***	(.114)	-.028***	(.007)
Area of *destination district* (natural log)	-.044	(.293)	-.022*	(.012)
Population density of *destination district* (natural log)	-.312	(.349)	.006	(.012)
Tractor owner (at least one) in *destination district* (GLSS 2013)	.646*	(.394)	.111*	(.064)
Tractor population in *destination district* (from GLSS 2013)	-.278	(.359)	-.070	(.065)
Average distance of destination district to other districts	.320	(.227)	.034**	(.015)
Different planting month in destination district	.372***	(.088)	.013***	(.004)
Agricultural area per worker (natural log)	-.131	(.180)	.008	(.007)
Night light intensity (natural log)	-.222	(.210)	-.004	(.007)
Dummy (home-districts)	Included		Included	
Dummy (sample-districts)	Included		Included	
Dummy (major-sample-districts)	Included		Included	
Agroclimatic variables PCs in destination district	Included		Included	
Region dummies of destination district	Included		Included	
Intercept	Included		Included	
Number of observations	70,720		70,720	
p-value (H_0: variables jointly insignificant)	.000		.000	

Source: Authors' estimations. Asterisks indicate the statistical significance *** 1% ** 5% * 10% †15%
Note: "Home district" if the destination district is the same as the home district of tractor owner.

7 Conclusions

Increased capital use in agriculture, including mechanization, is considered an integral process of agricultural transformation. Despite some recent emergence of medium-to-large scale farmers in SSA, as well as labor-movement out of agricultural sector (particularly youths), smallholders without substantial mechanization have remained the majority in the agricultural sector in countries like Ghana. Globally, mechanization has often been associated with large-scale farming given the complementarity between machine and land. The experiences in Asia in the last few decades, however, suggest that mechanization may grow even among smallholders before they transition into larger-scale farmers. These experiences have prompted the need to understand better how mechanization may be adopted by smallholders for whom the scope for exploiting complementarity between mechanization and land is limited.

Among potential factors, high-yielding biological technologies remain potentially important inducers of the adoption of mechanical technologies in the smallholder-dominant environment, because with limited scope for area expansion, higher returns to (and thus the demand for) farm power per unit of land are the primary source of demand for machines. However, empirical evidence on the roles of high-yielding biological technologies remains scarce, partly because of the difficulty in identifying exogenous variations which may affect mechanization adoptions only through yields. We attempted to fill this knowledge gap using the example of Ghana. We used novel instrumental variables based on agroclimatic similarity that captures the spatial spillover potentials of high-yielding biological technologies, derived using principal components of agroclimatic variables and the locations of plant-breeding institutes.

Our results are consistent with the hypotheses that, smallholders' adoptions of agricultural machinery at both extensive margins and intensive margins, are positively induced by the high-yielding potentials that are enhanced by greater agroclimatic similarity with plant-breeding locations. These linkages commonly hold for multiple-dimensions of agroclimatic similarity, as captured through several principal components of agroclimatic variables, indicating the robustness of the findings in the presence of potentially complex roles of agroclimatic factors on agriculture. These findings are consistent with the hypotheses that, higher-yield potentials also raise the returns to the use of agricultural machinery at both margins. Furthermore, using a set of multiple, unique, distinct datasets, we offered richer insights on how the improved supply-side efficiency might have strengthened the linkages between these demand-side factors and the actual machine-adoptions among smallholders.

Lastly, our analyses contributed to multiple strands of literature, not only on agricultural mechanization. We contributed to technology adoption literature through evidence on the determinants on adoptions at not only extensive margins but also intensive margins, roles of plant breeding and high-yielding technologies on agricultural and rural transformation, as well as the econometric literature that deals with factor analyses and instrumental variables.

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Appendix A: Regions in Ghana

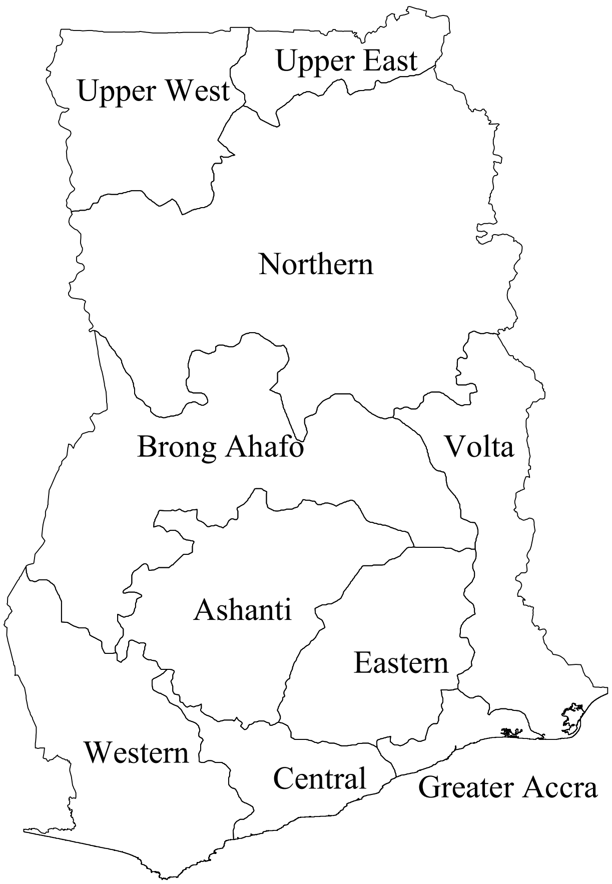


Figure 5. Regions in Ghana
Source: Authors.

Appendix B. Key descriptive information from IFPRI-SARI data

Table 18 summarizes the tractor use for different crops among samples in IFPRI-SARI data. Because of the nature of the sampling, maize is the most commonly grown crop and also for which tractors are most commonly used. Crops like rice, where grown, are also cultivated with tractors. IFPRI-SARI data provide detailed tractor use information on maize and rice plots, which we will use in our analyses.

Table 18. Tractor use for tillage and crops among samples of IFPRI-SARI data

Crops	All			Excluding tractor owners		
	% of sample farmers growing (a)	% of sample farmers using machines for tillage (b)	% using mechanized tillage (b / a)	% of sample farmers growing (a)	% of sample farmers using machines for tillage (b)	% using mechanized tillage (b / a)
Cowpea	27	18	67	24	14	56
Groundnuts	38	24	63	40	22	57
Maize	88	57	64	85	47	55
Rice	34	24	72	30	19	63
Soybean	29	22	75	27	18	67

Source: Authors based on IFPRI-SARI data.

Common use of tractors by operations

Table 19 and Table 20 summarize common uses of tractors for different operations revealed from IFPRI-SARI data. These tables provide figures from different samples (Table 19 for maize and rice farmers renting-in tractors, and Table 20 for those renting-out tractors). We show both tables, each with different sample, to cross-validate key patterns (and because IFPRI-SARI data are not nationally representative).

Table 19. Common use of tractors by operations (from user-side)

Operations	Maize					Rice				
	% doing this operation	% using tractors or animals	% using tractors	% hiring in tractors	Expense	% doing this operation	% using tractors or animals	% using tractors	% hiring in tractors	Expense
First Plowing	87	73	65	40	120	92	78	69	42	90
Second Plowing	11	11	8	3	16	13	13	11	5	14
Harrowing	3	3	2	1	4	14	14	13	5	13
Planting	99	0	0	0	1	97	9	8	3	8
Fertilizer application	88	0	0	0	0	69	0	0	0	0
Carrying from the plot to homestead	92	57	51	30	43	98	4	4	3	44
Shelling / threshing and packing	94	50	50	38	128	92	53	46	24	25

Source: Authors based on IFPRI-SARI data.

Table 20. Common use of tractors by operations (from service providers sample)

Operations	Tractor use (%)	Tractor use for hiring out (%)	Revenues from hiring out (Cedi / year) – within the same rainfall zone
Any farming activities	100	88	
First plowing	90	83	12905
Second plowing	30	20	867
Harrowing	16	10	379
Shelling maize	24	20	719

Source: Chapoto et al. (2014) for the percentage. Authors' calculations for revenues.

These tables collectively suggest that, rented-out tractors are most commonly used for plowing activities, in terms of adoptions at both extensive margins and intensive margins (expenses). Furthermore, second plowing and harrowing by manual labor or animals are rare, and are only adopted when tractors are adopted. While the rental of tractors for shelling is also somewhat common among maize farmers, this seems to be limited to particular crops like maize, and less common than plowing for other crops.

Extent of cross-district migrations for service provision

Table 21 presents the distribution of the number of districts operated by the tractor owners among IFPRI-SARI (2014) sample. Commonly (3/4 of sample), these tractor owners operate in more than 1 district, and ¼ of the sample operated in 5 or more districts in 2012. Similarly, about 16% of samples (= 5% + 4% + 7%) operated in districts in different rainfall zones than their own districts. These conditions suggest that, tractor owners commonly face options when deciding on which districts to operate, in addition to their home districts.

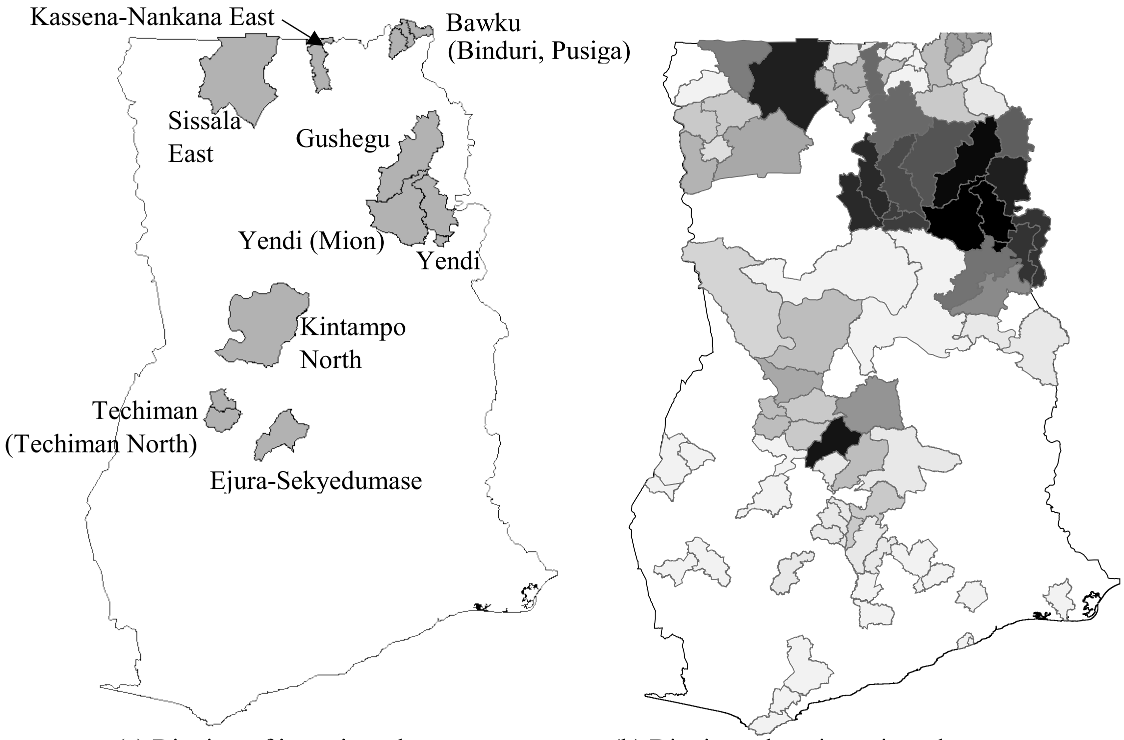
Table 21. Share (%) of service providers operating in different number of districts

Number of districts operated in 2012	All districts	Districts in different rainfall zones
1	23	5
2	22	4
3	17	7
4	14	
5 ~	25	

Source: Authors' calculations based on IFPRI-SARI (2014) data.

Among 16% of samples who also travel to different rainfall zones, Table 22 further informs how they make such travels. A majority of them travel to these rainfall zones every year (81%), and to the same districts in these zones (77%). More than half of them (58%) travel alone (instead of in a group with other service providers). Typically, they spend 2 months in the destination zone. Tractors are mostly transported on trucks (88%). In most cases (61%), both owners and operators travel together with the tractors. Finally, most of them obtain repair services and spare parts from local mechanics/welders or local dealers. These patterns suggest that by 2012, the mobility of tractor service providers has improved.

Figure 6 illustrates the 8 districts where interviewed tractor-owners are located, and all districts where they provided hiring services in 2013. It is important to note that, although a significant share of service provisions still concentrate in home districts, there are also active cross-district movements of these service providers.



(a) Districts of interviewed tractor owners

(b) Districts where interviewed tractor owners provide services (darker color = indicated by more interviewed tractor owners)

Figure 6. Districts where interviewed tractors provided service in 2013

Source: Authors based on IFPRI-SARI Data (2013).

Note: District names in parentheses are those in 2017, which were split from original districts after 2013.

Table 22. Migration patterns of tractor service providers to different rainfall zones (among those traveling to districts in different rainfall zones)

Categories	%
% migrating to different rainfall zones every year	81
% migrating to the same districts in the different rainfall zones every year	77
% migrating alone (instead of with other service providers)	58
Average days spent in destination zone	56
% transporting tractors – on trucks	88
% transporting tractors – drive on road	12
% by the mode of transportation	
- owner only	3
- owner & assistant only	5
- operators & assistant only	31
- operator & owner	25
- operator & assistant under owner / relative supervision	36
Who mostly service/repair your tractors in the migration/other rainfall zone?	
- (%) local mechanic/ welder	73
- (%) migrant mechanic / welder	27
Whom do you mostly buy your spare parts from in the migration zone?	
- (%) local dealer	73
- (%) migrant dealer	27

Source: Authors calculations from IFPRI-SARI (2014).

Further improvements in tractor access since 2006

Among the IFPRI-SARI (2014) sample, there are a few other indications of improved access to tractors in Ghana since 2006. Table 23 summarizes the share (%) of tractors obtained in either one of the 10 regional hubs (Accra, Kumasi, Tamale, Wa, Bolgatanga, Koforidua, Sunyani, Cape Coast, Ho, Sekondi), or one of the district capitals (which typically counted for 100 ~ 200 during the recall period and thus were more scattered), and the differences in these shares between tractors obtained up to 2005, and after 2005. Among all tractors, the shares of regional hubs have slightly decreased from 82% to 76%, while those of the district capital increased from 18% to 24%, among the sample. In particular, the patterns in regions outside Ashanti region, have been clearer and statistically significant. Therefore, while most tractors continued to be obtained at one of the regional hubs, they are also becoming increasingly available at the district capitals.

Table 23. Share (%) of tractors obtained from different locations

Locations	All sample		Ashanti Region sample		Other regions sample	
	Acquired up to 2005	Acquired after 2005	Acquired up to 2005	Acquired after 2005	Acquired up to 2005	Acquired after 2005
Regional hubs	82	76	67	56	95	85*
District capital	18	24	33	44	5	15*

Sources: Authors calculations from IFPRI-SARI (2014). Asterisk (*) indicate difference across periods is statistically significant at 10%.
Regional hubs = Accra, Kumasi, Tamale, Wa, Bolgatanga, Koforidua, Sunyani, Cape Coast, Ho, Sekondi.

Table 24 shows that, a majority of service providers (typically 70 – 80%) indicated that, they had provided more services in 2011 than 2010, and 2012 than 2011. While these figures need to be interpreted with cautions (eg., recency bias), they weakly indicate that the intensity of service provision per tractors had increased over time.

Table 24. % of tractor service providers providing more services in later years

Categories	% providing more services in 2012 than 2011	% providing more services in 2011 than 2010
Among those providing services for First Plowing	69	73
Among those providing services for Second Plowing	66	73
Among those providing services for Harrowing	83	79
Among those providing services for Shelling maize	83	86

Sources: Authors calculations from IFPRI-SARI (2014).

Lastly, Table 25 suggests that, in various regions, the private sector has become increasingly important source of information when purchasing tractors. In particular, regions outside Ashanti region, the share of samples reporting the private sector as the main source of information had increased from 75% (for tractors acquired up to 2005) to 86% (for tractors acquired after 2005). This pattern suggests that, the private-sector tractor markets have become increasingly efficient since 2006.

Table 25. Share (%) of source of information when purchasing tractors

Sources	All sample		Ashanti Region sample		Other Regions sample	
	Acquired up to 2005	Acquired after 2005	Acquired up to 2005	Acquired after 2005	Acquired up to 2005	Acquired after 2005
Government	16	12	7	6	25	14*
Others (private sector)	84	88	93	94	75	86*

Sources: Authors calculations from IFPRI-SARI (2014). Asterisk (*) indicate difference across periods is statistically significant at 10%.

Appendix C: agroclimatic similarity indicators through principal components

Table 26. Correlations between agroclimatic similarity indicators based on different principal components

		Principal components number on which agroclimatic similarity index is based									
		1	2	3	4	5	6	7	8	9	10
Principal components number on which agroclimatic similarity index is based	1	1.000									
	2	.283	1.000								
	3	-.015	.088	1.000							
	4	.081	.270	.131	1.000						
	5	.368	.083	-.073	.239	1.000					
	6	.025	.239	-.015	.586	.114	1.000				
	7	-.067	-.126	.014	-.066	-.057	-.155	1.000			
	8	.088	-.135	.057	-.094	.012	.050	-.185	1.000		
	9	-.074	.048	.037	-.066	-.138	-.053	.095	-.066	1.000	
	10	-.020	.033	-.070	.214	.066	.084	-.111	.002	-.052	1.000

Source: Authors.

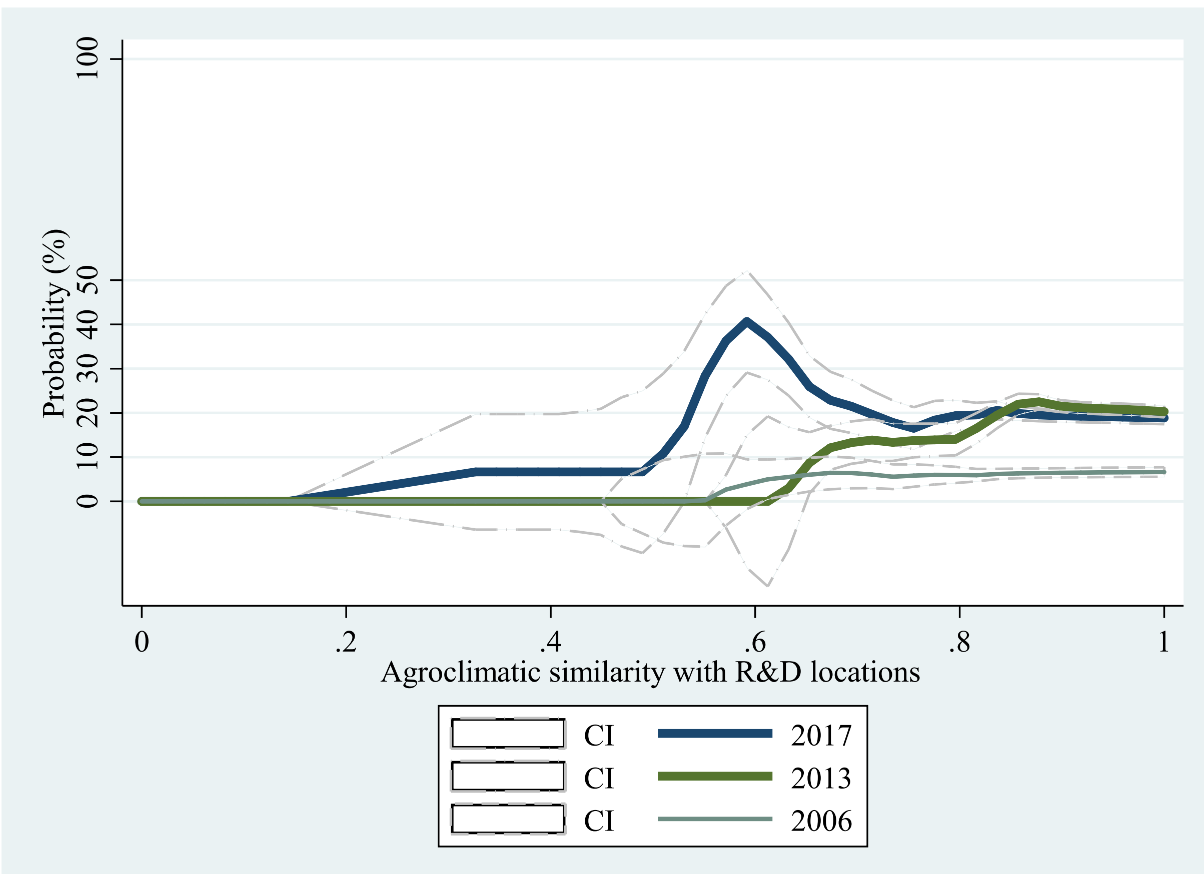


Figure 7. Agroclimatic similarity (with R&D locations) and probability of renting in agricultural machinery – based on the 4th principal component

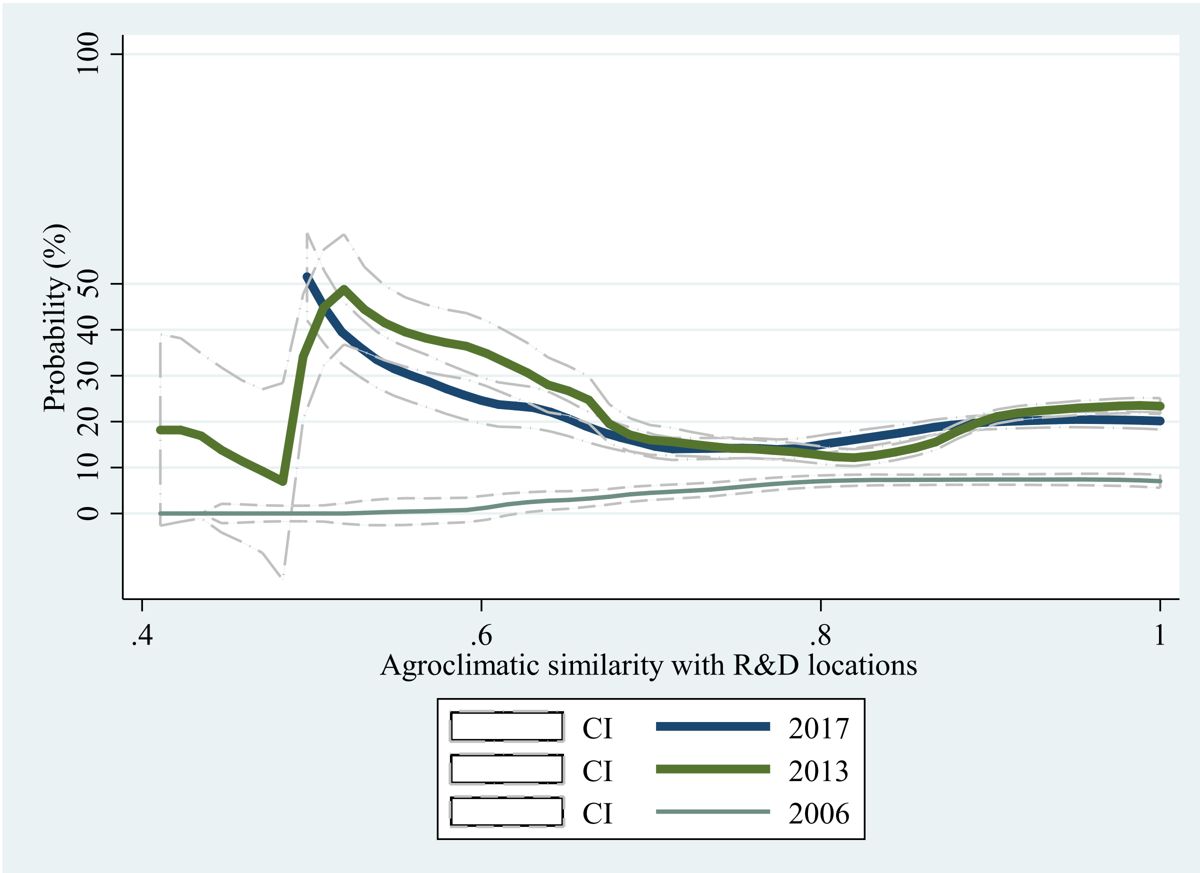


Figure 8. Agroclimatic similarity (with R&D locations) and probability of renting in agricultural machinery – based on the 5th principal component

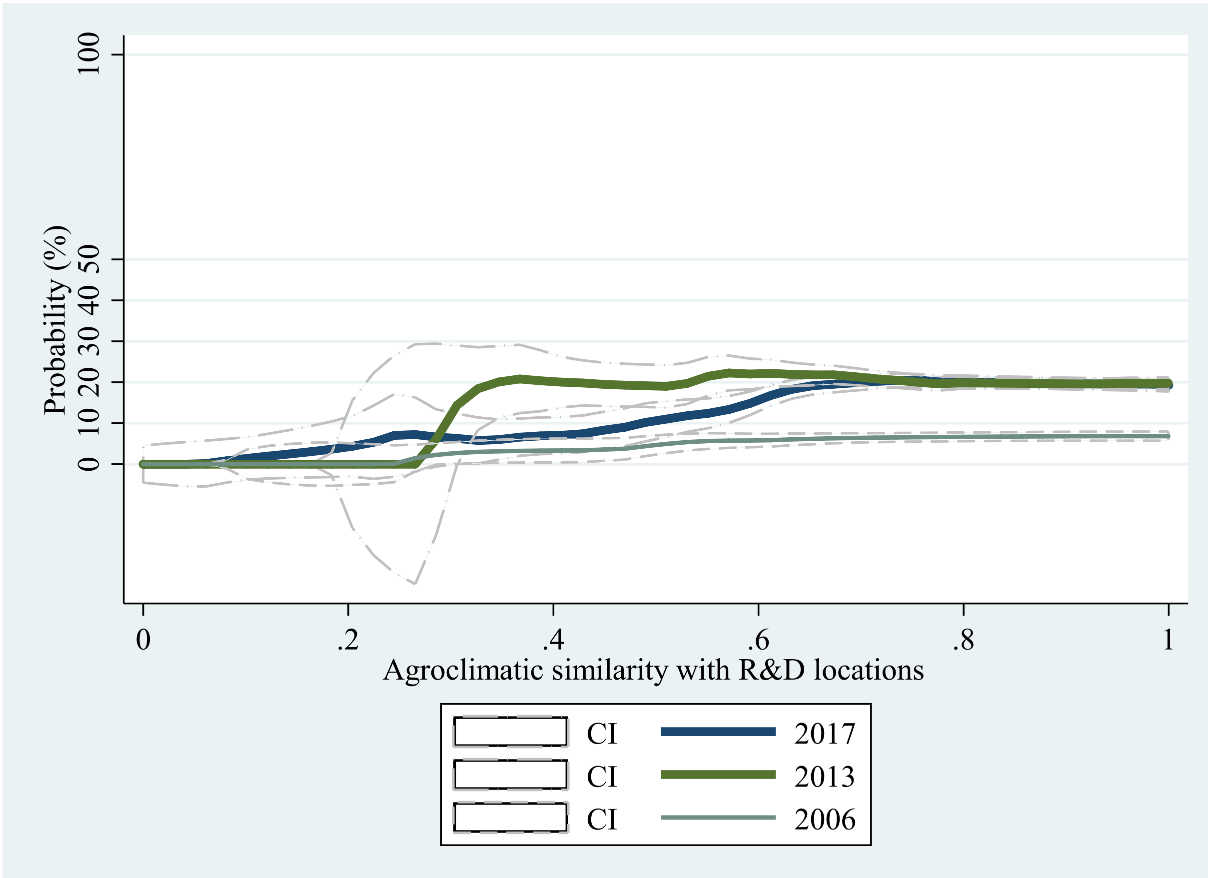


Figure 9. Agroclimatic similarity (with R&D locations) and probability of renting in agricultural machinery – based on the 6th principal component

Appendix D: Effects of agroclimatic similarity on yield

Table 27. Determinants of yield (among all samples) – effects of one-standard deviations of each variable on yield growth (1 = 100%)

Variables	Whole sample		< 10 ha	
	Coef.	Std.err[a]	Coef.	Std.err[a]
Ag similarity (PC 1)	.061	(.064)	.066	(.066)
Ag similarity (PC 2)	-.111	(.078)	-.105	(.080)
Ag similarity (PC 3)	.081	(.082)	.091	(.086)
Ag similarity (PC 4)	-.044	(.060)	-.037	(.061)
Ag similarity (PC 5)	-.138	(.110)	-.153	(.113)
Ag similarity (PC 6)	.256***	(.087)	**.307*****	(.089)
Farmland owned (ha, natural log)	-.029**	(.010)	-.013	(.011)
Distance to road / public transportation	-.015	(.010)	-.010	(.010)
Distance to market	.027***	(.010)	.025**	(.010)
Distance to extension office	-.015	(.010)	-.015	(.010)
Distance to the nearest plant breeding institute	-.026**	(.011)	-.025**	(.011)
Household size	.003	(.009)	-.002	(.009)
Age of head	-.045***	(.009)	-.044***	(.009)
Gender of head (female = 1)	-.050	(.010)	-.050***	(.010)
Education of head (years)	.027***	(.010)	.024**	(.011)
Livestock (value, natural log)	.042***	(.010)	.041***	(.010)
Non-productive assets (value, natural log)	.067***	(.010)	.071***	(.010)
Agricultural capital (value, natural log)	.018*	(.010)	.017	(.011)
Non-farm enterprise asset (value, natural log)	.003	(.009)	.002	(.009)
Farm wage (natural log)	-.039***	(.012)	-.032***	(.013)
Land value per hectare (natural log)	.013	(.011)	.012	(.011)
EA sample share of irrigators	.055***	(.011)	.060***	(.011)
EA sample share of fertilizer users	.116***	(.009)	.115***	(.010)
Land fragmentation index	.043***	(.009)	.046***	(.009)
Owning tractors (yes = 1)	.175**	(.078)	.177**	(.086)
EA sample share of tractor owners	.037***	(.009)	.038***	(.009)
Agroclimatic variables (6 PCs)	Included		Included	
Region dummies	Included		Included	
Sector dummy (rural / urban)	Included		Included	
Year dummy	Included		Included	
Intercept	Included		Included	
Number of observations	12,164		11,541	
p-value (H_0: variables jointly insignificant)	.000		.000	

Source: Authors' estimations. Asterisks indicate the statistical significance *** 1% ** 5% * 10% †15%

[a]Standard errors are based on 200 paired bootstrap.

Table 28. Determinants of rice yield among IFPRI-SARI data – effects of one-standard deviations of each variable on yield growth

Variables	owned farm size < 20ha		owned farm size < 10ha	
	Coef.	Std.err[a]	Coef.	Std.err[a]
Ag similarity (PC 1)	.041	(.080)	-.114	(.115)
Ag similarity (PC 2)	.106**	(.050)	.141**	(.070)
Ag similarity (PC 3)	-.067	(.054)	.019	(.058)
Ag similarity (PC 4)	-.175	(.121)	-.133	(.119)
Ag similarity (PC 5)	-.043	(.060)	-.017	(.066)
Ag similarity (PC 6)	.033	(.128)	.083	(.144)
Farmland owned (ha, natural log)	.010	(.050)	-.054	(.063)
Distance to the nearest 20k population town	-.058	(.080)	-.123	(.092)
Government extension as primary source (yes = 1)	.047	(.055)	.124**	(.059)
Distance to the nearest plant breeding institute	.159	(.176)	.435	(.267)
Household size	.059	(.061)	.060	(.062)
Age of head	.023	(.046)	.035	(.061)
Gender of head (female = 1)	-.149***	(.048)	-.132**	(.066)
Education of head (years)	.033	(.054)	.128	(.082)
Livestock (value, natural log)	-.038	(.045)	-.025	(.049)
Non-productive assets (value, natural log)	.660	(.527)	.310	(.457)
Agricultural capital (value, natural log)	-.679	(.540)	-.291	(.474)
Farm wage (natural log)	.050	(.053)	.008	(.069)
Land tenure security	-.092*	(.050)	-.049	(.059)
Village sample share of irrigators	.274***	(.090)	.221***	(.076)
Price of fertilizer (value, natural log)	.000	(.032)	-.004	(.049)
Village sample share of tractor owners	-.103	(.074)	-.068	(.078)
Land fragmentation index	.032	(.036)	.095	(.089)
Tractor owner (yes = 1)	.518*	(.277)	.307	(.362)
Agroclimatic variables (6 PC)	Included		Included	
District dummies	Included		Included	
Intercept	Included		Included	
Number of observations	385		252	
p-value (H_0: variables jointly insignificant)	.000		.000	

Source: Authors' estimations. Asterisks indicate the statistical significance *** 1% ** 5% * 10% [†]15%
[a]Standard errors are based on 200 paired bootstrap.

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