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The Roles of Agroclimatic Similarity and Returns on Scale in the Demand for Mechanization: Insights from Northern Nigeria

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ABSTRACT

Despite economic transformations and urbanization, declining shares of the workforce employed in the agricultural sector, and gradual growth of agricultural mechanization, production costs in the agricultural sector and food prices remain high in Nigeria relative to those in some of the other developing countries. Understanding how the adoption of mechanical technologies is related to agricultural productivity is therefore important for countries like Nigeria. Using farm household data from northern Nigeria as well as various spatial agroclimatic data, this study shows that the adoption of key mechanical technologies in Nigerian agriculture (animal traction, tractors, or both) has been high in areas that are more agroclimatically similar to the locations of agricultural research and development (R&D) stations, and this effect is heterogeneous, being particularly strong among relatively larger farms. Furthermore, such effects are likely to have been driven by the rise in returns on scale in the underlying production function caused by the adoption of these mechanical technologies. Agricultural mechanization, represented here as the switch from manual labor to animal traction and tractors, has been not only raising the average return on scale but also potentially magnifying the effects of productivity-enhancing public-sector R&D on spatial variations in agricultural productivity in countries like Nigeria.

Keywords: agricultural mechanization, agroclimatic similarity, returns on scale, inverse-probability weighting, Nigeria

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1. BACKGROUND

A growing number of developing countries, including those in Africa south of the Sahara, such as Nigeria, have experienced seeming economic transformations recently, characterized by declining shares of the gross domestic product (GDP) originating from the agricultural sector and rising shares from the nonagricultural sector, accompanied by movement of the labor force out of the agricultural sector (ACET 2014). Accompanying such transformations, agricultural mechanization has gradually progressed in countries like Nigeria, particularly intermediate modes of mechanization such as animal traction. However, as described in this paper, the adoption of mechanical technologies in Nigeria is still relatively limited at the intensive margins. At the same time, the seeming economic transformation has not been accompanied by substantial agricultural intensification in Nigeria as it has in many other countries outside Africa. Consequently, food prices, including farmgate prices of major crops, have remained high in Nigeria (see, for example, for rice, Gyimah-Brempong, Johnson, and Takeshima 2016), preventing economic transformation from translating into real income growth and poverty reduction, as well as hampering any rise in the overall competitiveness of the economy. Therefore, understanding the agricultural productivity growth that is both causing and triggered by such a gradual growth of mechanization is important for a country like Nigeria.

Public-sector agricultural research and development (R&D) aimed at raising overall productivity, including plant breeding, is a potentially important determinant for the adoption of agricultural mechanization because, historically, the public sector has played a relatively more important role in plant breeding than in R&D for other inputs, including mechanical technologies, which have been relatively more directly transferable from abroad (Evenson

1988).[1] Because of their public sector–led nature, agricultural R&D systems have provided significant exogenous variations in agricultural productivity in addition to the existing agroclimatic diversity in countries like Nigeria, whereby agricultural productivity is positively associated with "agroclimatic similarity," the similarity in agroclimatic conditions between the areas where farms are located and the areas where major plant breeding institutes are located (Takeshima and Nasir 2017).[2] Furthermore, agricultural R&D centered on plant breeding has often raised the total factor productivity (TFP) (Evenson and Gollin 2003; Walker and Alwang 2015) with potentially Hicks-neutral effects, so that it has also often raised the returns on farm power inputs, complementing rather than substituting for the use of mechanical technologies. Such mechanisms may partly explain why agricultural mechanization has grown rapidly in developing countries in Asia despite land scarcity and persistent smallholder dominance there, primarily through the spread of small-scale machinery (Biggs and Justice 2015).

Agricultural mechanization itself has been generally scale biased, often complementary to farm size; that is, adoption of mechanical technologies is often higher among larger farms than among smaller farms. A recent study has suggested that in Nepal, tractor adoption directly raises the return on scale (ROS) of the underlying production function (Takeshima 2017). These phenomena suggest that the interaction effects of agroclimatic similarity and production scale (particularly farm size) play an important role in the adoption of mechanical technologies.

[1] This comparison is, of course, in relative terms. The public sector still plays an important role in the development of mechanical technologies that can be used in the country (Diao, Silver, and Takeshima 2017).

[2] The concept of "agroclimatic similarity" was originally developed by Bazzi and others (2016), who investigated the transferability to destination locations of migrants' skills developed in origin locations, and how this transferability is affected by the similarity of agroclimatic conditions in the origin and destination locations. Takeshima and Nasir (2017) extended this concept to the transferability of agricultural technologies (particularly varietal technologies) from agricultural R&D institutions to each farmer's location, and how it might depend on the similarity in agroclimatic conditions between the areas where these agricultural R&D institutions are located and those where farmers are located. Its measurement is described in Section 4 of this paper.

Although such interaction effects on the adoption of mechanical technologies are intuitive, evidence has been scarce, especially in countries like Nigeria. Formally investigating these relationships is important for many reasons. If the interaction effects of agroclimatic similarity and farm size are significant, even if agroclimatic similarity alone has, on average, an insignificant effect, there may be considerable heterogeneity in its effects by different production scales (farm sizes). If mechanical technologies have an important scale bias, then their effects are likely to be magnified as mechanization progresses. It is also important to formally investigate whether the rise in ROS is directly attributable to the adoption of mechanical technologies, because such a rise can also be caused by factors other than mechanization. For example, several studies have associated the emergence of large farms in developing countries with the spread of improved varieties that are resistant to pests (Deininger and Byerlee 2012), specialization, land consolidation (Wan and Cheung 2001), and a change of crop mix (Cramb 2011). However, if the adoption of mechanization technologies is directly responsible for the rise in ROS, then the rise in ROS and subsequent effects in the agricultural sector would be expected to kick in at a specific stage of agricultural development—that is, the stage when the mechanical technologies are becoming increasingly adopted, which has historically been relatively short in many countries[3]—and not at any other stages.

This paper tests these hypotheses using the data of farm households in Nigeria from the Living Standards Measurement Study–Integrated Surveys on Agriculture (LSMS-ISA) (LSMS, various years) as well as the locations of agricultural R&D stations that focus on plant breeding and various spatial agroclimatic data. Our results are consistent with the aforementioned

[3] For example, in the United States, tractor adoption rates, as measured by the percentage of farmers owning tractors, increased from 14 percent to 50 percent in 20 years (1930 to 1950) (Olmstead & Rhode 2001). In Japan, the adoption of power tillers and of planting and harvesting machines increased from about 10 percent to almost 100 percent in 15 years (1955–1965) (Economic Planning Agency 1962; Barker et al. 1985).

hypotheses in that the adoption of key mechanical technologies in agriculture in Nigeria (animal traction, tractors, or both) has been high in areas with higher agroclimatic similarity to agricultural R&D stations, and this effect has been heterogeneous, being particularly strong among relatively larger farms. Furthermore, these effects are likely to have been driven by the fact that the adoption of these mechanical technologies has been directly causing the rise in ROS in the underlying production function.

This study contributes to various strands of the literature. It sheds new light on the adoption patterns of mechanical technologies by investigating the linkages between farming-system intensification and agricultural mechanization (Binswanger 1986; Diao, Silver, and Takeshima 2016). It also relates to the literature on animal traction in developing countries (Lawrence and Pearson 2002), including countries in Africa (Jaeger and Matlon 1990; Jansen 1993; Ehui and Polson 1993), as well as the literature on tractors (Diao et al. 2014; Takeshima, Nin-Pratt, and Diao 2013). This study also complements the literature assessing the ROS in agricultural production and its variations over time and space (Hayami and Kawagoe 1989; Kislev and Peterson 1996; Basu 2008; Takeshima 2017; Takeshima, Houssou, and Diao 2017). The paper also links agricultural mechanization to agricultural R&D in Africa on technologies other than machinery, such as plant breeding, which raises varietal technology and overall productivity (Walker and Alwang 2015).

This study does not directly address the questions and hypotheses raised by these past studies. Instead, it provides evidence that connects these strands of literature, highlighting that agricultural transformation has historically involved a rise in overall ROS (with both positive and potentially negative effects), and that domestic public-sector R&D has had important effects on the geographic variations in agricultural productivity. Agricultural mechanization, represented here as the switch from manual labor to animal traction and tractors, has been not only raising the average ROS but also potentially magnifying the role of productivity-enhancing public-sector R&D on the spatial variations in agricultural productivity in countries like Nigeria.

This paper is structured in the following way. Section 2 briefly describes the past agricultural mechanization progress in Nigeria. Section 3 describes the empirical framework. Section 4 describes the dataset and variables as well as presenting key descriptive statistics. Section 5 discusses the results and implications, and Section 6 concludes.

2. MECHANIZATION PROGRESS IN NIGERIA

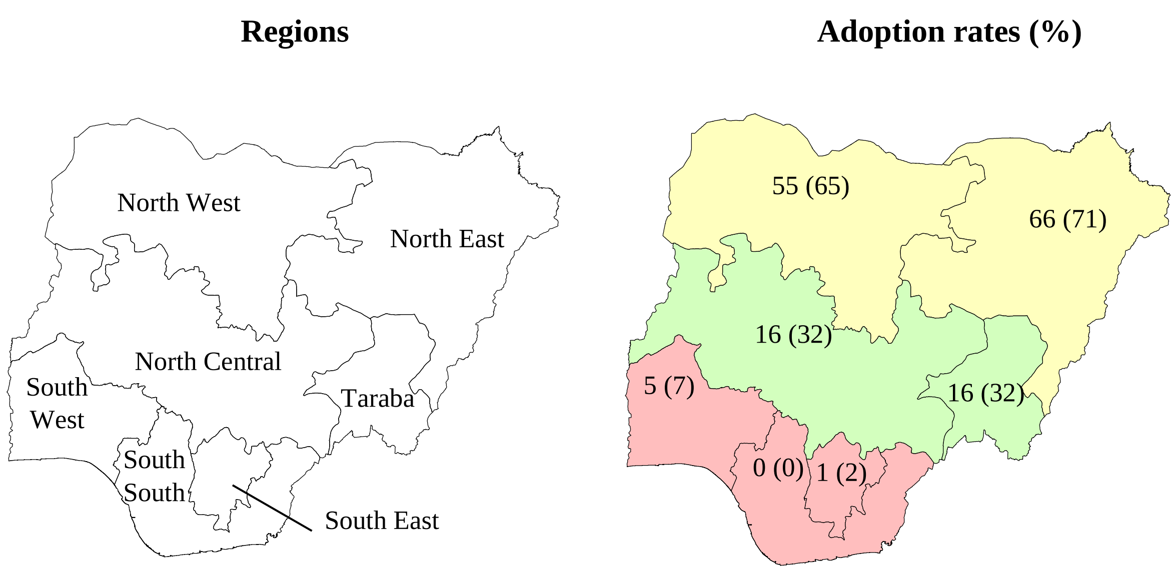
Table 2.1 summarizes the historical evolution of the adoption of mechanical technologies in Nigerian agriculture, especially animal traction and tractors, as well as the country's overall economic transformation and expansion of arable land over the past several decades. The adoption of mechanical technologies in agriculture has grown gradually in Nigeria, although a significant portion of it has been the growing adoption of animal traction. The increase in adoption rates of animal traction has been particularly pronounced in the North West and North East zones, where the share of area cultivated with animal traction increased from less than 10 percent in the 1980s to almost two-thirds in the period beginning in 2010 (Figure 2.1 shows the locations of these zones in Nigeria, as well as the current adoption rates). At the national level, the share of area with animal traction has increased from around 3 percent to about 5 percent in the 1980s and to about 32 percent in the last period depicted. Although the share of area with tractors has remained relatively stagnant since the 1980s (hovering around 10 percent), the total area cultivated with tractors is likely to have increased as well during this period, given that total arable land has increased by almost 50 percent since the 1980s (from 23 million ha to 34 million ha).

Table 2.1 Economic structure, arable land, and level of tractor and animal traction use over time in Nigeria

Variable	1960–1969	1970–1979	1980–1989	1990–1999	2000–2009	from 2010 on[d]
GDP share (%)—services	33	40	30	24	24	53
GDP share (%)—industry	13	27	34	43	40	25
GDP share (%)—agriculture	54	33	36	33	35	22
Arable land (million ha)	28	26	23	32	35	34
% of area mechanized with …						
Tractors	1[b]	5[b]	9	10	9	7
Animal traction			3–5[c]			32
Animal traction (north)[a]			6–10			66
Animal traction or tractors						38
Animal traction or tractors (north)						68

Source: Share of area mechanized with tractors from Dunham (1980); Ugwuishiwu and Onwualu (2009); and Azogu (2009). Share of area mechanized through animal traction from Dunham (1980); Philipps, Abalu, and Ingawa (1986); Jansen (1993); and LSMS (various years). GDP shares from Sackey et al. (2013) for 1960s and 1970s, World Bank (2016) for the rest. Arable land from FAO (2016).
Note: [a] North = North West and North East zones, excluding Taraba State. [b] Extrapolated by the author using the number of tractors in use and area of arable land from FAO (2016) and the data for the 1980 from Dunham (1980). [c] The proportions from the period beginning in 2010 are applied, based on the fact that animal traction use in the south of the country has been almost nonexistent. [d] The figures for 2010 and later are likely to differ from those for the previous years due to rebasing conducted recently.

Figure 2.1 Region locations and adoption rates (percentages) of mechanical technologies (animal traction, tractors, or both) in Nigeria (averages over 2010/2011, 2012/2013, and 2015/2016)



Source: Author’s calculations based on LSMS (various years).
Note: Figures in parentheses are adoption rates weighted by cultivated area.

Although it is beyond the scope of this paper to examine the causes of the spread of mechanical technologies, and of animal traction in particular, Table 2.1 suggests that this spread has been associated with a deepening economic transformation characterized by the growth of the nonagricultural sector, particularly the service sector. The share of the service sector in GDP had grown to exceed 50 percent by the period beginning in 2010, along with a growing labor scarcity and rising labor costs felt by the agricultural sector despite the rapid population growth that has raised the demand for more intensive cultivation.

Although the adoption rates of animal traction have risen in Nigeria, particularly in the North West and the North East zones, its use intensity on average is still limited. Table 2.2 shows the animal traction use intensity (animal-days per farm household) in northern Nigeria and in other selected countries during the periods right before each of these countries experienced significant growth in tractor use as a substitute for animal traction. Table 2.2 suggests that the use intensity of animal traction in Nigeria has been relatively low (less than 10 animal-days per farm) compared with that of the other countries shown, including Bangladesh and Japan, where tillage was much more intensive, using larger numbers of animals for multiple rounds of tillage in early days of the agricultural transformation. These conditions suggest that there is likely to be scope for Nigeria to further intensify its use of farm power.

Table 2.2 Animal traction use intensity

Country/region	Reference year(s)	Animal traction intensity (animal-days per farm household per year)	Source
Nigeria—North West	2010–2013	6	LSMS (2010/11, 2012/13)
Nigeria—North East	2010–2013	9	LSMS (2010/11, 2012/13)
Bangladesh	Early 1990s	90	Mandal and Parker (1995)
Japan	1950s	30	Economic Planning Agency (1962)
Thailand	1991	15	Pryor (1993)
United States	1930s	100 (including other uses of animals)	Jasny (1935)

Source: Author’s compilations based on the studies listed.

Importantly, the increased use of animal traction, particularly in northern Nigeria, has also reportedly been induced in part by the introduction of other improved technologies, particularly the improved maize varieties that have spread since the 1970s and are more responsive to more intensive land preparation and other farm power uses (Goldman and Smith 1995; Smith et al. 1994). Such mechanisms have important implications for mechanization growth in African countries like Nigeria, where investments in agricultural R&D, including plant breeding, have been considerably limited, particularly in the last few decades (Walker and Alwang 2015; Flaherty et al. 2010; Takeshima 2014; Takeshima and Maji 2016). However, little empirical evidence exists that points to such agricultural R&D as an important determinant of agricultural mechanization. This apparent knowledge gap further motivates the empirical analysis in this paper.

3. EMPIRICAL FRAMEWORK[4]

One of the common measures of ROS is the sum of the output elasticities of all inputs in a production function (Kislev and Peterson 1996). The effect of the adoption of mechanical technologies (animal traction or tractors) on ROS can be estimated using the following framework.[5] We start by illustrating the condition for a farm household that belongs to one of two production systems: (1) with mechanized technologies (denoted as regime $R = 1$) and (2) without mechanized technologies ($R = 0$). Agricultural production, Y, for each farm household is realized in one of the Rs so that

$$Y = \begin{cases} f_1(K_1; A) \text{ if } R = 1 \\ f_0(K_0; A) \text{ if } R = 0 \end{cases}. \tag{1}$$

In equation (1), f_R is a regime-specific production function with vector K_R of inputs / production factors, given agroclimatic and socioeconomic conditions A. Farm households decide to adopt mechanical technologies, or not, by choosing R and K_R that maximize their utility, U, which depends on agricultural profit, π:

$$\max_{R, K_R} U(\pi), \tag{2}$$

where

$$\pi = R \cdot [f_1 \cdot (K_1; A) - c_1(\omega, K_1)] + (1 - R) \cdot [f_0 \cdot (K_0; A) - c_0(\omega, K_0)]. \tag{3}$$

In equation (3), $c_R(\omega, K_R)$ is the cost of using inputs and production factors K_R given ω (factors affecting inputs costs, including the opportunity costs of family labor), standardized by setting the price of composite outputs at 1.

Utility maximization problems (2) and (3) are solved with a set of constraints (including liquidity constraints),

$$g_R(K_R, A, \omega, \eta) \geq 0 \ , \forall R, \tag{4}$$

[4] The descriptions in this section largely draw on Takeshima (2017).
[5] Our analyses treat animal traction and tractors jointly as "mechanical technologies" instead of distinguishing them because, as shown in the previous section, the adoption rate of tractors is considerably lower than the adoption rate of animal traction in Nigeria, and the data are not suitable for analyzing their differential effects. Furthermore, a farm typology analysis by Takeshima, Nin-Pratt, and Diao (2013) revealed that animal traction and tractors may be generally used as substitutes, particularly in northern Nigeria, with the switch from animal traction to tractors not associated with substantial changes in the production system.

where η is a set of factors that affect the liquidity of the farm household. Importantly, both c_R and g_R vary across regime R.

The optimization problems above lead to the Lagrange function $\mathcal{L}_R$,

$$\mathcal{L}_R = U[f_R(K_R; A) - c_R(\omega, K_R)] + \lambda_R \cdot g_R(K_R, A, \omega, \eta), \forall R, \tag{5}$$

where λ_R is the Lagrange multiplier. The optimal solutions for K_R^* (asterisks indicate the solution values) satisfy the corresponding Kuhn-Tucker conditions. Because the Kuhn-Tucker conditions depend on f_R, c_R, g_R, A, ω, and η, and parameters defining f_R, c_R, and g_R are also functions of A, ω, and η, our empirical models are the following reduced-form equations:

$$R^* = r(f_R, c_R, g_R, A, \omega, \eta) = r(A, \omega, \eta) \text{ and} \tag{6}$$

$$K_R^* = k(f_R, c_R, g_R, A, \omega, \eta, R^*) = r(A, \omega, \eta, R^*), \tag{7}$$

with respective functions r and k. Observed output Y_R^* is related to K_R^* through structural equation f_R, so that $Y_R^* = f_R(K_R^*; A, R^*)$.

The Roles of Agroclimatic Similarity and Farm Size in the Adoption of Mechanical Technologies

Suppose an increased agroclimatic similarity with agricultural R&D institutions leads to a Hicks-neutral productivity increase through Δ, so that production function f_R is proportionally shifted to $\Delta \cdot f_R$. Even when the adoption of mechanical technologies has no effect on f_R (so that $f_1 \equiv f_0$), the increase in productivity through Δ will increase the optimal use of K_1, which includes farm power, because the marginal returns from using K_R, $\frac{\partial f_R}{\partial K_R}$, rise for all values of K_R relative to the marginal cost of using K_R, $\frac{\partial c_R}{\partial K_R}$. At the same time, the mechanical technologies are more efficient at supplying greater farm power. The higher the farm power use, K_R, the lower $\frac{\partial c_1}{\partial K_1}$ is than $\frac{\partial c_0}{\partial K_0}$, relatively speaking. Therefore, Hicks-neutral productivity growth, represented by Δ, is more likely to induce a switch from regime 0 to regime 1 as Δ rises and as optimal farm power use, K_1, rises.

Furthermore, farm power use is generally positively associated with the farm size. Therefore, a 1-unit increase in Δ generally leads to a greater increase in optimal farm power use among large farms than among smaller farms. Therefore, larger farms are more likely to see their optimal farm power use exceed the threshold at which the switch from regime 0 to 1 is induced. Such mechanisms suggest that there is a positive interaction effect of Δ and farm size on the probability of switching from regime 0 to regime 1, that is, the probability of adopting mechanical technologies.

Generally, these relationships become further reinforced if the adoption of mechanical technologies raises ROS so that f_1 exhibits greater ROS than f_0. This effect happens because the effects of Δ on the marginal productivity of K_1 in regime 1, $\frac{\partial f}{\partial K_1}$, become relatively greater at higher K_1 than at lower K_1. Therefore, if the adoption of mechanical technologies also raises ROS in f_1, the aforementioned interaction effects of Δ and farm size are likely to become stronger.

Empirical Approach

Effects of Agroclimatic Similarity and Farm Size on the Adoption of Animal Traction or Tractors

The first empirical model estimates equation (6) in a somewhat more structured way. Specifically, following the conceptual framework above, we estimate (6) through a panel fixed-effects linear probability model, using agroclimatic similarity, farm size, and their interaction as key variables, as well as other control variables:

$$R_{it} = \alpha + \alpha_x \cdot (A_{it}, \omega_{it}, \eta_{it}) + r_i + v_{it}, \tag{8}$$

where i and t are households and survey rounds, respectively; α and α_x are estimated parameters; r_i is unobserved time-invariant household-specific effects; v_{it} is idiosyncratic errors; and $(A_{it}, \omega_{it}, \eta_{it})$ is a vector of a subset of exogenous variables (including agroclimatic similarity, farm size, and their interaction) that are time variant. Parameter α also includes a dummy variable for the survey round. For simplicity, we suppress subscripts *i* and *t* hereafter.

Effects of the Adoption of Animal Traction, Tractors, or Both on Returns on Scale

Two types of endogeneity issues are associated with the framework described above: the endogeneity due to farm households' self-selection to adopt mechanical technologies and the endogeneity in observed inputs / factor use decisions in estimating the production function. Following recent studies such as the one by Takeshima (2017), we employ the inverse probability–weighted generalized method of moments (IPW-GMM) to address these issues jointly.

Specifically, we first estimate the probability that the farm household adopts mechanical technologies (animal traction or tractors) through probit,

$$\text{Probability}\ (R^* = 1|Z) = \hat{p} = \Phi(Z\gamma) = \int_{-\infty}^{Z\gamma} \phi(v)dv, \tag{9}$$

where $Z = A$, ω, and η; $\hat{p}$ is the predicted probability of the adoption of mechanical technologies; and γ is the set of parameters to be estimated. Φ and ϕ are the standard normal distribution function and standard normal density function, respectively, and v is the element for the latter. Equation (9) is estimated simply to obtain $\hat{p}$, and the determinants of adoption are investigated by equation (8).

We then estimate f_R and its corresponding ROS, ρ_R, for each R, given the observed Y, R, K_R, A, ω, and η. Specifically, we estimate the Cobb-Douglas production function

$$\ln Y = \beta_0 + \sum_j \beta_j \ln K_j + \beta_A A + \varepsilon, \tag{10}$$

in which βs are parameters to be estimated (with corresponding subscripts); ε is the idiosyncratic error term; and j = labor, land, agricultural equipment, value of livestock, and other cash expenses (including expenses on hired animal traction or tractors). Then $\widehat{\rho_R} = \sum_j \widehat{\beta_J}$.

The IPW-GMM is operationalized by estimating the β variables in equation (10) through

$$\hat{\beta} = \arg\min_{\beta} \left[E\left(\frac{m}{\sqrt{\hat{p}}}\right)\right] \widehat{W} \left[E\left(\frac{m}{\sqrt{\hat{p}}}\right)\right]' \tag{11}$$

for the adopters of mechanical technologies and

$$\hat{\beta} = \arg\min_{\beta} \left[E\left(\frac{m}{\sqrt{1-\hat{p}}}\right)\right] \widehat{W} \left[E\left(\frac{m}{\sqrt{1-\hat{p}}}\right)\right]' \tag{12}$$

for nonadopters, where E is the expectation over samples; $\widehat{W}$ is the suitable weighting matrix estimated in the generalized method of moments; and $m(\cdot)$ is the moment condition,

$$m(\cdot) = Z'\left[\ln Y - \left(\beta_0 + \sum_j \beta_j \ln K_j + \beta_A A\right)\right]. \tag{13}$$

IPW-GMM is "doubly robust" (Robins and Rotnitzky 1995) because the overall model is consistent as long as either the model of the propensity score, $\hat{p}$, or the model of the production function is consistent, even when the other model is misspecified.

Other Specification Issues

Although our primary dataset, LSMS-ISA (LSMS, various years), provides panel data for farm households, our estimation of ROS by equations (9) through (13) treats them as pooled cross-section data because ROS is often regarded as a long-run rather than a short-run concept, and cross-section data (with methods addressing endogeneity) may be more appropriate than fixed-effects and first-difference models, which are more suitable for capturing short-run effects (Basu 2008; Takeshima 2017). This approach treats the same farm households in different rounds of the survey as different farm households, due to changes over time in land endowments and demographics as well as unobserved individual-specific effects, including ability or management skills. This treatment is also suitable for the application of IPW-GMM, which requires estimation of regime-specific production functions using samples in each regime, R, and allows farm households to switch regime between survey rounds. Similar approaches have been used in other studies, including Takeshima and colleagues (2017).

4. DATA AND VARIABLES

The primary data source used in this analysis is the LSMS-ISA (LSMS, various years), which was collected jointly by the National Bureau of Statistics of Nigeria and the World Bank. The data consist of a total of 5,000 panel households interviewed in three waves (2010/2011, 2012/2013, and 2015/2016) and selected across each of six geopolitical zones in Nigeria. The samples were selected through stratified sampling methods in which 10 randomly selected households within each of 500 enumeration areas (EAs) were interviewed.

Our analyses focus on a subsample of the LSMS-ISA, specifically, the farm households that (1) reported information on at least one farm plot in each of the three waves and (2) were located in northern Nigeria (including the North West, North East, and North Central zones). We focus on northern Nigeria because the adoption rates of mechanical technologies in the southern area (the South East, South South, and South West zones) are very low and its farming systems (based on root and tree crops) are quite different from those in northern Nigeria (based on cereals).

Furthermore, we exclude irrigated farms because their shares among all farm households are quite small (less than 5 percent) and their production characteristics are very different from those of the rest of the farm households. Thus, including them in the samples could highly complicate the estimations of production characteristics such as ROS. Similarly, we exclude households in EAs with no or all samples adopting animal traction, because unobserved characteristics of these EAs might be considerably different from those of other EAs, and thus their inclusion could complicate the determinants of adoption and its effects on ROS. Households without EA locations or farm sizes were also excluded, because our analyses rely on information about various agroclimatic conditions that are extracted based on the households' locations, and because farm size is one of the important factors associated with ROS. A total sample of 3,569 households from the three survey rounds combined is used as the starting sample. For estimating the production function, we also excluded a small number of samples that lacked information on agricultural production values.

In addition, inverse probability weighting (IPW) can be susceptible to extreme values of propensities, that is, the samples with $\hat{p}$ close to 0 or 1 (Busso, DiNardo, and McCrary 2014). We therefore limit the samples for the estimation of the production function in equation (10) to those with $0.01 < \hat{p} < 0.99$. This step further reduces the combined number of samples for the estimation of equation (10) by approximately 5–10 percent.

This study uses various agroclimatic data in addition to the LSMS-ISA. Historical rainfall data and slope of the land are provided in the LSMS-ISA dataset. Solar radiation is obtained from the US National Aeronautics and Space Administration (NASA 2017). Data on wind speed at 10 meters above ground are obtained from the Climatic Research Unit of the University of East Anglia (CRU 2017). Terrain ruggedness is calculated using elevation data from GTOPO30 (USGS 1996) applied to a formula by Riley, DeGloria, and Elliot (1999). Soil-related data, including bulk density, organic carbon content, cation exchange capacity, and sand and silt composition (percentages) are taken from 1-km resolution soil mapping data (ISRIC 2013; Hengl et al. 2014). Rainfall in April and May of the LSMS-ISA survey years was extracted from data of the US National Oceanic and Atmospheric Administration (NOAA 2017). Shares of local land area under pasture are estimates based on Ramankutty and others (2008). The Euclidean distance to the nearest major river is calculated from World Wildlife Fund data (2006), and distance to the nearest dam is based on data from the Food and Agriculture Organization of the United Nations (FAO 2015). Finally, Euclidean distance to the nearest major agricultural research station (ARS) is from Takeshima and Nasir (2017).

Output and Input Variables

The variable Y, agricultural outputs, is measured as the total real value of all crops produced by the household. We calculate this variable based on the output figures and sales prices of each commodity, as reported by farmers. The value of nonsales uses of crops, such as household consumption, are imputed from the local prices of those crops. Use of production values is appropriate in Nigeria, where a typical farm household grows many crops and, because of a low share of certified seeds and infrequent seed replacement, the quality of varieties can vary considerably, even when the same crop variety is grown.

The variable K_R consists of land; labor; agricultural capital (equipment and animals); and other expenses including the values of all nonlabor inputs such as chemical fertilizer, agrochemicals, and hired-in mechanization services. Labor, land, and other expenses are treated as endogenous because they are likely to be affected by idiosyncratic shocks, and agricultural capital is treated as exogenous because it is likely to be fixed in the short term. The labor variable is constructed using information on self-employment in the agricultural sector reported over 12 months. Because the LSMS-ISA asked households for such information for the 12 months prior to postplanting and for the period between the postplanting and the postharvest surveys, the latter approximately 6 months, we converted the information for postplanting to 6-month equivalents by simply halving it, and then took the average of the postplanting and postharvest surveys. Construction of the labor variable also involved applying certain conversion factors for the children and elderly in the household in order to calculate adult equivalents. Specifically, we multiplied by 0.75 and 0.50 for elderly household members (above 60 years of age) and for children (below 20 years of age), respectively, following Djurfeldt (2013). We also tested slightly different conversion factors and found that the results were generally robust against different factors. This family labor was combined with information on hired-in labor for planting, weeding, and harvesting to generate an overall labor variable. Treating the labor variable as one of the endogenous variables also mitigates the measurement errors often associated with farm labor.

Agricultural capital includes the real value of agricultural equipment and the real value of livestock evaluated at local market prices. In the production function, livestock holdings, which provide draft power through animal traction as well as livestock products, are used as one of the production factors.[6]

[6] The effects of animal traction provided by rented animals, as well as the effects of rented tractors, are captured in the "other expenses" categories, in a method similar to that used by Takeshima (2017).

Agroclimatic Similarity

As was mentioned earlier, the variables A include "agroclimatic similarity" for northern Nigeria, obtained from Takeshima and Nasir (2017). It is constructed as a measure of the similarity between the area where each household is located and the area where the nearest plant breeding institution or substation is located, in terms of the soil, hydrological, and climate conditions described above. As in Takeshima and Nasir (2017), it is calculated by applying a formula used in the literature (for example, Bazzi et al. 2016), where a single indicator is constructed as a weighted sum of the similarity measures for each of the soil, hydrological, and climate factors.

Specifically, agroclimatic similarity is constructed in the following way. Following Takeshima and Nasir (2017), a raw similarity index for household i with respect to the breeding institute B ($D_{i.B}$) is

$$D_{i.B} = -\sum_{\theta} w_{\theta}(\left|A_i^{\theta} - A_B^{\theta}\right|), \tag{14}$$

where A_i^{θ} and A_B^{θ} are the values of key agroclimatic parameters θ in the areas where farm household i and breeding institute B, respectively, are located. $\left|A_i^{\theta} - A_B^{\theta}\right|$ is the absolute deviation. The weight for each θ (w_{θ}) captures the effect of the similarity of θ on the overall similarity of i's location to that of B. Following Bazzi and others (2016) and Takeshima and Nasir (2017), sample average values of θ are used as w_{θ}, so that absolute deviations are standardized relative to the unit of θ. $D_{i.B}$ is therefore the weighted sum of the absolute difference in the values of parameter θ between i and B. With the negative "$-$" added in front of the summation operator in equation (14), an increase in $D_{i.B}$ indicates an increase in agroclimatic similarity.

The overall similarity index for household i (D_i), then, is

$$D_i = f(D_{i,B}), \tag{15}$$

in which f denotes various functions that translate $D_{i.B}$ to D_i. We primarily present the case in which f is the average, so that $D_i = \sum_B D_{i.B}/N_B$, where N_B is the number of reference breeding institutes or stations. We then present the robustness of the results using different fs, such as the maximum and the average weighted by the number of improved varieties released (more details are provided in Section 5). Simply for ease of interpretation, D_i is then standardized so that its values are distributed between 0 and 1, with 0 being the least similar and 1 the most similar.

Our primary specifications use the reference locations of key breeding institutes—Maiduguri, Kano, Zaria, Badeggi, Ibadan, and Umudike—in view of the concentrations of released improved varieties at these institutes (Takeshima and Nasir 2017, Table 1). However, we also try different values for D_i by incorporating not only these major breeding institutes but also all the research outstations that belong to these institutes, as well as other national agricultural research institutes that focus on research other than breeding (detailed lists of these outstations are provided in Takeshima and Nasir 2017, Appendix).

The key agroclimatic parameters, θ, consist of three types: the first is climate-related parameters (annual rainfall, wind speed, and solar radiation), the second is soil-related parameters (cation exchange, acidity, proportion of sand, proportion of silt, organic carbon content, bulk density), and the third is topography-related parameters (terrain ruggedness, slope). As in Takeshima and Nasir (2017), these are expanded from Bazzi and colleagues (2016) to account for potentially important agroclimatic conditions in the Nigerian context by adding wind speed and solar radiation. Wind is an important yield-limiting factor for many crops and also an important cause of soil erosion (Tittonell and Giller 2013). Solar radiation can vary considerably within Nigeria, with a substantial effect on the yield of many crops, including rice (Takeshima and Bakare 2016). We also originally included various other parameters but found that they are highly correlated with the above-mentioned parameters. We therefore focus on the aforementioned set of agroclimatic parameters.

Other Exogenous Variables

In addition to the agroclimatic similarity index, the *A* variables also include raw values of the agroclimatic parameters, θ, mentioned above. Inclusion of these raw values as variables allows us to estimate their effects on the production frontier (the production that is possible at the highest efficiency), whereas the effects of the agroclimatic similarity index will be captured as the deviation from the production frontier (reflecting inefficiency). The *A* variables also include short-term rainfall in the pre-land-preparation periods (April and May) as well as the distances to the nearest river, dam, and ARS. Short-term rainfall in April and May of each survey round controls for the effects of weather factors on agricultural production in each year.[7] Euclidean distances to rivers and dams proxy hydrological conditions on the soils that can affect agricultural production even under rainfed systems. Euclidean distance to the nearest ARS captures the diffusion of improved production practices to areas where farm households are located. Note that the Euclidean distance to an ARS captures effects that are different from the effects of agroclimatic similarity with an ARS.

Variables ω include key demographic characteristics (number of male and female adult household members, number of child household members, and age of household head), which generally affect the opportunity costs of labor. The share of educated working-age household members (those who have received at least some years of formal education) are also included to capture both the potential effects of education on agricultural labor productivity and the opportunity costs of using these family workers for agricultural production (rather than having them earn incomes from the nonagricultural sector).

ω also includes farmland endowments proxied by two types of farm areas: those that have been purchased outright and those distributed by village authorities (such as chiefs). These types of areas are selected because they are likely to be exogenous to farm households' decisions to adopt mechanical technologies and other production inputs. ω also includes the market prices and (opportunity) costs of various inputs, including real prices of beef[8] and milk, animal traction rental cost per day, real price of chemical fertilizer, and farm wages. An indicator of local pasture area per head of large livestock (heifer, steer, cow, bull, ox, donkey, horse, camel) is also included to proxy the cost of feeding the animals.

[7] The rainfall in these months is particularly important because it often affects the timing of plowing, which often comes immediately following the major rains, and any delay in this tillage and subsequent planting can lead to substantial yield reductions (Tittonell and Giller 2013).

[8] For example, higher beef prices sometimes have a negative impact on the utilization of oxen for cultivation (Ehui and Polson 1993).

Distances to the nearest market and administrative center are also included to account for other potential factors that affect access to markets and other institutional infrastructure.

Variables ω also include the sample shares of farm households using animal traction in the EA, as well as EA average animal traction use intensity. These factors are included to account for the (potentially nonlinear) effects of various unobserved external factors that may affect the net benefits of adoption, such as the knowledge required to use mechanical technologies and the accessibility of hiring services. These variables are also included in order to consider the surveyed farm households' positions among adopters and nonadopters of mechanical technologies in areas with similar intensification potentials for such mechanization. These positions tend to vary considerably across locations due to unobserved factors other than observed agroclimatic conditions, including spatial variations in the breeds of draft animals or brands of tractors, location-specific animal diseases (Lawrence and Pearson 2002), and limiting factors for machinery.

Variables η include household asset endowments, which often constitute liquid wealth that can be used to overcome credit constraints for purchasing certain inputs or services.

Most variables ω and η are also used as excluded instrumental variables (IVs) in Z in equation (13) to instrument endogenous input variables in production function estimations. For nonadopters of mechanical technologies, certain variables (average animal traction use intensity in the EA, animal traction rental costs) are dropped, because they are no longer relevant IVs for these households. Variables with highly skewed distributions are transformed into natural log forms so that their effects on corresponding dependent variables are more representative of the ranges of their values. Last, dummy variables indicating each round of the LSMS-ISA are included to control for year-specific factors.

All monetary values are deflated by the average local prices of rice and *gari* (a granular product of cassava), two of the most commonly consumed staples in Nigeria (Gyimah-Brempong, Johnson, and Takeshima 2016), to control for any potential variations in the price index across space.

Descriptive Statistics

Table 4.1 summarizes the mean value of each variable used in the analysis and its statistical significance between the samples of adopters and nonadopters. It shows the descriptive statistics with and without probability weights ($\hat{p}$), which are estimated in the next section, because this method demonstrates improvements in the matching properties of the samples realized through the IPW process. With probability weights, the differences become statistically insignificant for most exogenous variables, suggesting that the IPW process successfully generated matched samples. Any differences in production functions and ROS between the two groups, as shown in the next section, can thereby be more precisely attributed to the adoption of mechanical technologies.

Table 4.1 Descriptive statistics (raw samples and inverse probability–weighted samples)

Category/variable	Raw sample		IPW-adjusted sample	
	Adopters	Non adopters	Adopters	Non adopters
Sample size	1,784	1,785	1,784	1,785
Endogenous variables				
ln (Real revenue of outputs)	9.104	8.702**	9.067	8.977
ln (Labor use) (person-day per year)	5.547	5.562	5.531	5.439
ln (Land) (square meters)	9.245	9.019**	9.200	8.980 *
ln (Other expenditures for purchased inputs)	3.592	2.261**	3.316	2.774 *
Exogenous variables				
EA sample share of mechanical technology adopters	0.666	0.323**	0.520	0.533
EA sample share of mechanical technology adopters, squared	0.528	0.165**	0.374	0.387
ln (real local price of beef)	2.048	2.065	2.056	2.066
ln (real local price of milk)	0.388	0.318**	0.363	0.395
ln (real value of agricultural equipment owned)	1.953	1.562**	1.720	1.843
ln (real value of livestock owned)	5.627	3.927**	4.803	4.953
Pasture area per head of livestock (index)	0.187	0.309**	0.254	0.242
EA average animal traction use intensity (animal-days/farm)	8.341	2.410**	6.148	7.919
ln (animal traction rental cost per day)	3.218	3.235	3.242	3.227 †
ln (number of male adult household members ≥ 20 years old)	0.219	0.160*	0.190	0.158
ln (number of female adult household members ≥ 20 years old)	0.268	0.244	0.265	0.184
ln (number of child household members)	1.105	0.917**	1.071	0.983
Age of household head	48.019	48.540	48.019	47.205
Distance to market (minutes of travel time)	70.2595	71.154	71.413	71.793
Distance to administrative center (minutes of travel time)	94.289	92.155	93.545	91.847
ln (area of farmland purchased outright), ha	-2.913	-3.530**	-3.185	-3.336
ln (area of farmland distributed by the chief), ha	2.876	2.487†	2.754	2.592
ln (real price of chemical fertilizer)	0.022	-0.007	0.011	0.060
ln (real daily farm wage for an adult male worker)	1.665	1.666	1.664	1.660
ln (real value of household assets)	7.976	7.580**	7.867	7.847

Table 4.1 Continued

Category/variable	Raw sample		IPW-adjusted sample	
	Adopters	Non adopters	Adopter s	Non adopters
Sample size	1,784	1,785	1,784	1,785
Share of noneducated working-age household members	0.462	0.511**	0.490	0.518
Soil bulk density (MT/m^3)	1.383	1.347**	1.371	1.373
Soil silt composition (%)	20.953	20.466*	20.824	20.374
Soil sand composition (%)	64.371	62.752**	63.900	64.331
Soil acidity (pH)	6.403	6.260**	6.360	6.331
Soil organic contents (g/kg of soil)	7.024	7.816**	7.300	7.256
Euclidean distance to ARS (geographic minutes)	2.509	2.725**	2.575	2.538
Euclidean distance to nearest river (geographic minutes)	0.0173	0.0165*	0.01707	0.01668
Euclidean distance to dam (geographic minutes)	0.6261	0.6444	0.629	0.638
Rainfall (historical average, long term, mm)	872.531	931.193**	895.970	889.985
Rainfall (historical standard deviation, mm)	151.154	149.770†	151.955	149.757 *
Rainfall in April (mm)	20.589	23.208**	21.00	19.87
Rainfall in May (mm)	63.4	67.0†	64.45	64.60
Wind (10-meter height, annual average, m/s)	2.959	2.883**	2.916	2.928
Solar radiation (kWh/m^2, annual average)	5.802	5.742**	5.774	5.775
Slope (%)	2.078	2.640**	2.241	2.234
Terrain ruggedness (index)	34.750	39.622**	35.073	35.673
% surveyed in Wave 1 (2010/2011)	27.77	37.67**	34.00	31.31
% surveyed in Wave 2 (2012/2013)	38.42	30.79**	32.60	37.16
% surveyed in Wave 3 (2015/2016)	33.80	31.54	33.40	31.53

Source: Authors' estimations based on LSMS (various years).

Note: Statistical significance: † 10 percent, * 5 percent, ** 1 percent. ARS = agricultural research station; IPW = inverse probability weighting. All monetary values are deflated by the average local prices of rice and *gari* (a granular product of cassava), two of the most commonly consumed staples in Nigeria (Gyimah-Brempong et al. 2016), to control for potential variations in the price index across space.

5. RESULTS

Relationship of Adoption Rates to Agroclimatic Similarity and Farm Size

Table 5.1 shows the estimated effects of farm size, agroclimatic similarity, and their interaction on the adoption of mechanical technologies (animal traction, tractors, or both). Following Takeshima and Nasir (2017), we also show the robustness of the estimated results across various measures of agroclimatic similarity. Specifically, we use the following four versions: (a) "primary specifications," where D_i in equation (15) is the average, so that $D_i = \sum_B D_{i.B} / N_B$, in which N_B is the number of reference breeding institutes or stations; (b) specifications using the maximum similarity among all breeding institutes, where D_i is the similarity index with the most similar breeding institute, that is, $D_i = \max(D_{i,B})$; (c) specifications using the average similarity weighted by the number of developed varieties released, where $D_i = \sum_B V_B D_{i.B} / N_B$, with V_B being the total number of improved varieties released by breeding institute B (based on Takeshima and Nasir 2017, Table 1); and (d) specifications using all outstations of breeding institutes, which is similar to (a), except that D_i is the average of similarity with respect to all outstations.

Table 5.1 Determinants of adopting mechanical technologies, panel fixed effects, linear probability model (elasticities)

Measure of agroclimatic similarity	Designation	North West and North East (excl. Taraba State)		Northern Nigeria	
		Farm size	Ln (farm size)	Farm size	Ln (farm size)
Primary specifications (a)	*D*	0.159**	0.225**	0.075**	0.142**
	F	0.097*	0.139**	0.085*	0.132**
	D × *F*	0.078*	0.087*	0.071*	0.090**
Robustness check (b) using the maximum similarity among all breeding institutes	*F*	0.044†	0.099**	0.043†	0.086**
	D × *F*	0.027	0.047*	0.030†	0.045**
Robustness check (c) using the average similarity weighted by the number of developed varieties released	*F*	0.093**	0.144**	0.055†	0.113**
	D × *F*	0.072*	0.091**	0.046	0.072**
Robustness check (d) using all outstations of breeding institutes	*F*	0.112*	0.164**	0.010	0.084*
	D × *F*	0.092*	0.111**	0.002	0.044

Source: Author's estimations based on LSMS (various years).
Note: Statistical significance: † 10 percent, * 5 percent, ** 1 percent. *D* = agroclimatic similarity; *F* = size of farm purchased outright or distributed by the village.

Furthermore, we also show the results with and without the natural log transformation of farm size, as well as with and without the North Central zone as part of the sample. In terms of agroclimatic conditions and farming systems, the North Central zone is more similar to the North West and North East zones than the southern zones are, but it still exhibits some differences.[9] Full results of the primary specifications are presented in Table A.1 in the Appendix. Figures in Table 5.1 are shown as elasticities. For example, 0.097 means that a 1-percent increase in farm size leads to a 0.097-percent higher probability of adopting mechanical technologies.

Note that the effects of agroclimatic similarity, which is time invariant, are estimated by regressing the predicted household fixed effects on all time-invariant variables that were dropped from the panel fixed-effect specifications. However, we show only the effect of agroclimatic similarity (without its interaction with farm size) for the primary specifications (the first row of Table 5.1) because the properties of the aforementioned methodology of regressing predicted fixed effects on time-invariant variables are not clearly established in the literature. Nevertheless, this methodology still provides some indications of the effects of these time-invariant variables, such as agroclimatic similarity, on the adoption rates of mechanical technologies.

Overall, the set of results in Table 5.1 suggests that, for a broad range of measures, both agroclimatic similarity and greater farm size, and importantly, their interactive effects, are consistently strong determinants that positively affect the adoption of mechanical technologies (animal traction, tractors, or both).

Importantly, the results in Table 5.1 do not mean that the agroclimatic similarity indexes are capturing the effects of other potentially correlated variables. For example, Tables 5.2 and 5.3 show the Spearman rank correlations between the agroclimatic similarity indexes and farm size, and between the agroclimatic similarity indexes and distance to the administrative center, respectively. Although one may

[9] Based on the standard farming system classification by Dixon, Gulliver, and Gibbon (2001), the North West and North East zones of Nigeria straddle the pastoral system, the agropastoral millet/sorghum system, and the cereal–root crops mixed system, whereas the North Central zone mainly uses the cereal–root crops mixed system.

argue that average farm size may be smaller in areas with high agroclimatic similarity (because higher productivity there may lead to higher population growth or in-migration from elsewhere), no strong correlations are found between these variables (indicated by correlation coefficients that are much smaller than 1 in Table 5.2). Similarly, though one may argue that agroclimatic similarity may be higher in areas closer to administrative centers because research stations are sometimes located in such administrative centers, these correlations are quite weak (that is, the correlation coefficients in Table 5.3 are also much smaller than 1). Therefore, it is unlikely that the strong effects of agroclimatic similarity in Table 5.1 are wrongly capturing the effects of other variables that are strongly correlated with agroclimatic similarity.

Table 5.2 Limited correlations between agroclimatic similarity and average exogenous farm size (Spearman rank correlations)

Measure of agroclimatic similarity	Northern Nigeria	North West and North East zones (excluding Taraba State)
Primary specifications (a)	0.021	0.023
Robustness check (b) using the maximum similarity among all breeding institutes	0.065	0.053
Robustness check (c) using the average similarity weighted by the number of developed varieties released	0.033	0.041
Robustness check (d) using all outstations of breeding institutes	-0.022	0.018

Source: Author’s estimations based on LSMS (various years).

Table 5.3 Limited correlations between agroclimatic similarity and distance to the nearest administrative center (Spearman rank correlations)

Measure of agroclimatic similarity	Northern Nigeria	North West and North East zones (excluding Taraba State)
Primary specifications (a)	0.203	0.121
Robustness check (b) using the maximum similarity among all breeding institutes	0.246	0.158
Robustness check (c) using the average similarity weighted by the number of developed varieties released	0.155	0.066
Robustness check (d) using all outstations of breeding institutes	0.036	-0.044

Source: Author’s estimations based on LSMS (various years).

Other Key Determinants

The primary interests of this paper regarding the determinants of the adoption of mechanical technologies are agroclimatic similarity to the breeding institute and farm size, summarized in Table 5.1. The other key determinants, based on the full results shown in Appendix Table A.1, include the following. The probability of adopting a mechanical technology is higher for households with greater values of livestock owned, possibly because mechanical technology may be associated with owning more animals that can provide traction, and possibly because of higher demand for intensification to produce feed crops. Higher rental costs generally discourage adoption, as expected. Higher chemical fertilizer prices also discourage adoption. Although chemical fertilizer may often be considered a substitute for mechanical technology, here a higher fertilizer price may discourage the adoption of mechanical technologies because cultivating a larger area with a mechanical technology also requires a greater amount of fertilizer. Adoption rates are also higher in areas more suitable for irrigation, which is proxied by a greater share of farmers in the EA who use irrigation. More capital-endowed farm households are also more likely to adopt mechanical technologies, possibly because agricultural equipment may complement draft animal use by facilitating various operations on farms initially plowed by draft animals or tractors, which tend to be larger, or by raising the productivity of the equipment when it is attached to animals or tractors (Jansen 1993). Higher rainfall in April is also found to induce more adoption of mechanical technologies, possibly because it may increase the vegetation in the soil, requiring more intensive plowing at the beginning of the production season. A steeper slope on one's farmland discourages the use of mechanical technologies, possibly because soil erosion from intensive plowing may be more severe. Greater household assets may encourage adoption of mechanical technologies by relieving the liquidity constraints on purchasing more inputs to farm more area more intensively using mechanical technologies. A greater share of educated working-age household members may encourage adoption of mechanical technologies, possibly due to higher opportunity costs for family labor. Female-headed households are less likely to adopt mechanical technologies, possibly due to various constraints they face in accessing modern inputs in general.

Attribution of Rising Returns on Scale to the Adoption of Mechanical Technologies

Table 5.4 shows the estimated effects of the adoption of mechanical technologies (animal traction, tractors, or both) on ROS, as measured through the effects on underlying production functions. Effects are shown for various measures of agroclimatic similarity for robustness-check purposes. All test specifications suggest that the input variables deemed endogenous are indeed so, and the specifications with included and excluded IVs satisfy necessary conditions for the consistency of the estimated parameters.

Table 5.4 Effects of adoption of mechanical technologies on production functions and returns on scale

Variable/category	Agroclimatic similarity index							
	(a)		(b)		(c)		(d)	
	Adopters	Nonadopters	Adopters	Nonadopters	Adopters	Nonadopters	Adopters	Nonadopters
Production function coefficients								
Land	0.649**	0.019	0.599**	0.177	0.657**	0.004	0.642**	-0.034
	(0.217)	(0.206)	(0.228)	(0.212)	(0.216)	(0.204)	(0.217)	(0.206)
Labor	0.327	0.055	0.359	0.067	0.317	0.053	0.324	0.062
	(0.265)	(0.121)	(0.282)	(0.107)	(0.265)	(0.125)	(0.265)	(0.121)
Livestock	0.000	0.025	0.008	0.018	0.001	0.025	0.001	0.026
	(0.021)	(0.017)	(0.022)	(0.017)	(0.022)	(0.017)	(0.022)	(0.017)
Agricultural equipment	0.067	0.123**	0.042	0.118**	0.067	0.124**	0.067	0.124**
	(0.043)	(0.043)	(0.047)	(0.044)	(0.043)	(0.043)	(0.043)	(0.043)
Other expenditures for purchased inputs	0.160**	0.245**	0.182**	0.281**	0.165**	0.245**	0.161**	0.248**
	(0.051)	(0.062)	(0.059)	(0.066)	(0.051)	(0.062)	(0.051)	(0.062)
Agroclimatic similarity	0.150*	0.292**	0.173*	0.090	0.001**	0.002**	0.152*	0.299**
	(.072)	(0.067)	(0.071)	(0.061)	(0.001)	(0.001)	(0.074)	(0.067)
ROS	1.203**	0.469*	1.157**	0.662	1.208**	0.451*	1.195**	0.426*
	(0.271)	(0.191)	(0.268)	(0.184)	(0.271)	(0.189)	(0.272)	(0.190)
Z-value for the significance of the difference in ROS ($\widehat{\rho_R}$)[a]	2.214		1.523		2.291		2.318	
No. of observations	1,662	1,718	1,662	1,718	1,662	1,718	1,662	1,718
p-value								
H_0: Land, labor, and other expenditures jointly exogenous[b]	.000	.000	.000	.000	.000	.000	.000	.000
H_0: Model is not overidentified[c]	.317	.378.	.394	.131	.332	.427	.328	.379
H_0: Model suffers from weak identification[d]	.002	.082	.002	.005	.003	.080	.002	.073
H_0: Variables are jointly insignificant	.000	.000	.000	.000	.000	.000	.000	.000

Source: Authors' estimations based on LSMS (various years).

Note: Statistical significance: † 10 percent, * 5 percent, ** 1 percent. ROS = return on scale. Standard errors are adjusted for possible within–enumeration area correlations of idiosyncratic shocks. Standard errors reported do not account for the potential complications of multiple steps involved with the estimations, as described in the literature on the inverse probability–weighted generalized method of moments (IPW-GMM). [a] Statistical significance is based on the raw standard errors, which do not account for the potential complications of multiple steps involved in the estimations. The standard errors of inverse probability weighting, particularly of multiple-step estimation methods like ours (IPW-GMM), have not yet been developed in the literature (Imbens and Wooldridge 2009). [b] Endogeneity test is based on Hausman (1978). [c] Based on Hansen *J*-statistics. [d] Based on Kleibergen and Paap (2006).

The findings suggest that adoption of mechanical technologies (animal traction, tractors, or both) significantly raises the ROS in agricultural production at the farm household level. The estimated ROS ($\widehat{\rho_R}$) is generally in the range of 0.5 among the IPW sample of nonadopters, whereas it is on the order of 1.0 among the IPW sample of adopters. Although each ROS is not necessarily representative of each type of farm household, the differences in $\widehat{\rho_R}$ between these two groups are internally consistent estimators.

The same interpretations apply to the estimated coefficients (output elasticities) of each input. Although their differences are less precisely estimated, results generally suggest that the increase in ROS from the adoption of mechanical technologies largely accrues to increased output elasticities of land (generally 0.6 among adopters as opposed to near 0 among nonadopters). These findings are consistent with the hypothesis that the positive interaction effects of agroclimatic similarity with farm size on adoption (Table 5.1) are partly driven by the ROS-raising effects shown in Table 5.4.

It is important to note that the estimated production functions and corresponding ROS hold only for the currently prevailing production scales in the samples (typical range of farm size, labor uses, use intensity of other purchased inputs, and agricultural capital intensity). The ROS can be different for other farm households that are not represented in the sample analyzed in this paper, or it could change as a significant segment of farm households evolves into production systems on different scales.

Other Key Determinants of Total Factor Productivity

Our primary interest is the ROS, and particularly the difference in ROS between adopters and nonadopters of mechanical technologies. As mentioned above, the results for adopters or nonadopters by themselves are not representative because the results are based on an IPW sample. However, we will briefly interpret the full results, shown in Table A.2 in the appendix. Coefficients of all variables other than inputs and production factors can be roughly interpreted as their effects on TFP.

Agroclimatic similarity to the nearest plant breeding station is positively associated with TFP, consistent with earlier descriptions. Greater soil bulk density may lower TFP, possibly because of reduced aeration and the general farm power requirements for plowing, such as the use of animal traction (Jaeger and Matlon 1990). Productivity is also higher in areas with historically higher and more stable rainfall, as expected. Greater rainfall in May seems negatively associated with TFP, possibly because it may increase the prevalence of pests during the main production season that follows. Greater wind is also negatively associated with TFP because it tends to cause higher evapotranspiration and reduced moisture and as well as increased land degradation (World Bank 2007; Tittonell and Giller 2013). A greater plot slope is positively associated with TFP, possibly reflecting the fact that farming systems often range from midslope with lighter soils to lowland with heavier soils, such that TFP at midslope may be originally high (Binswanger-Mkhize and Savastano 2017). Rugged terrain, on the other hand, is negatively associated with TFP, often raising the transaction costs for trade and for movement of inputs and other factors (Nunn and Puga 2012). A younger household head is also found to be associated with a higher TFP. Finally, a greater share of noneducated household members is also, surprisingly, positively associated with TFP, possibly because the lack of education may reflect these individuals' longer engagement and comparative familiarity with farming, compared with more educated household members, who may have been less engaged in farming.

6. CONCLUSIONS

There has been a knowledge gap regarding how agricultural mechanization in countries like Nigeria has both been induced by and affected agricultural productivity. In particular, despite the important role the public sector has historically played in raising overall productivity and improving technologies through R&D in plant breeding, little knowledge existed in Nigeria about how this role might have affected the adoption of mechanical technologies. Furthermore, despite the general agreement that agricultural mechanization is associated with a greater ROS in agriculture, little has been known about whether the former causes the latter, rather than the other way around, limiting our understanding of how ROS evolves during the agricultural transformation process.

This paper partly fills this knowledge gap, using farm household data from Nigeria as well as various spatial agroclimatic data. The results suggest that the adoption of key agricultural mechanization technologies in Nigeria (animal traction, tractors, or both) has been higher in areas with higher agroclimatic similarity with agricultural R&D stations, and this effect is heterogeneous, being particularly strong among relatively larger farms. Furthermore, these effects are likely to have been driven by the fact that the adoption of these mechanical technologies has been directly causing a rise in ROS in the underlying production function. Agricultural mechanization, represented here as the switch from manual labor to animal traction and tractors, has been not only raising the average ROS but also potentially magnifying the effects of productivity-enhancing public-sector R&D on spatial variations in agricultural productivity in countries like Nigeria.

In Nigeria, both intensification-driven demand and scale effects–induced demand are jointly important determinants of the adoption of mechanical technologies. Even intermediate mechanization technologies such as animal traction have important scale effects, suggesting that the agricultural sector in Nigeria has undergone significant changes in the comparative advantages among farms with different scales.

Methodologically, the results show that agroclimatic similarity indicators, which have not yet been widely used in the literature, are important in understanding the potential demand for and adoption of mechanical technologies, as well as other inputs, in countries like Nigeria. This outcome suggests that not only the spatial variations in agroclimatic conditions but also the spatial variations in public-sector R&D activities are important factors in explaining the spatial variations in demand for mechanization in Nigeria.

The findings have important policy implications. First, they are consistent with the hypothesis that in Nigeria, overall agricultural production technologies, including varietal technologies that critically affect the returns on farm power use and are often generated through public-sector agricultural R&D, are still inferior and have been holding back further mechanization growth at the intensive margins, including the substitution of tractors for animal traction at a wider scale.

Second, the findings further suggest the importance of continued efforts in public-sector social science R&D related to mechanization. In particular, these efforts involve gathering more information and data, required for a better understanding of spatial variations in the demand for mechanization. For example, the sample size of the Nigeria LSMS-ISA is 5,000 in each round. This sample is likely to be insufficient for countries like Nigeria, where there are on the order of 20 million farm households operating in considerably diverse production environments. Alternative data with larger samples, such as an agricultural census, has not been gathered for many years in Nigeria (Hatzenbuehler, Abbott, and Abdoulaye 2017) and often includes only the ownership of draft animals or machines, rarely reporting on their actual uses, often due to insufficient support for the enumeration process. It is also important to invest in public-sector research to better understand the potential implications of the effects of rising ROS in the agricultural sector, partly driven by the adoption of mechanical technologies. In theory, such a rise in ROS gradually shifts the comparative advantage from small farms to larger farms and from small-scale operations to larger-scale operations. In such an environment, smallholders can benefit greatly from either renting out or selling their farms to larger farmers while specializing in nonfarm or off-farm activities (including working as hired labor on larger farms), and through potentially reduced food prices brought about by increased exploration of economies of scale in the agricultural sector. However, such transitions may be difficult for certain groups of farm household members (for example, older farmers with fewer outside opportunities) and for farms with weak land tenure security. A recent study in Nepal (Takeshima 2018) has suggested that asset-poor smallholders tend to continue subsistence farming, potentially for fear of food market risks (such as price risks). It will remain important for the public sector to design appropriate policies that can facilitate such transitions.

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APPENDIX: ROBUSTNESS CHECKS

Table A.1 Determinants of the adoption of mechanical technologies (animal traction, tractors, or both), linear probability model, primary specifications

Variable	North West and North East zones, excluding Taraba State	Northern Nigeria
Agroclimatic similarity to location of research station (σ)	0.225** (0.035)	0.142** (0.026)
Farm area purchased outright or distributed by chief (F)	0.139** (0.039)	0.132** (0.030)
σ × F	0.087* (0.035)	0.090** (0.027)
ln (real local price of beef)	0.101 (0.162)	-0.041 (0.127)
ln (real local price of milk)	0.009 (0.015)	0.013 (0.012)
Pasture area per head of livestock (index)	-0.006 (0.008)	0.001 (0.008)
ln (real value of livestock owned)	0.135** (0.020)	0.112** (0.018)
ln (animal traction rental cost per day)	-0.086 (0.064)	-0.246** (0.066)
ln (number of male adult household members ≥ 20 years old)	-0.007 (0.008)	-0.005 (0.004)
ln (number of female adult household members ≥ 20 years old)	0.000 (0.005)	0.004 (0.005)
ln (number of child household members)	0.009 (0.020)	0.013 (0.014)
Age of household head	0.129 (0.116)	0.063 (0.121)
Distance to market (minutes of travel time)	-0.833 (1.159)	0.520 (0.486)
Distance to administrative center (minutes of travel time)	-0.141 (0.130)	-0.268 (0.177)
ln (real price of chemical fertilizer)	-0.001 (0.001)	-0.001* (0.000)
ln (real daily farm wage for an adult male worker)	0.389 (0.403)	0.260 (0.226)
EA sample share of farmers using irrigation	0.026** (0.008)	0.021** (0.007)
ln (real value of agricultural equipment owned)	0.098** (0.018)	0.067** (0.018)
Rainfall in April (mm)	0.029* (0.014)	0.007 (0.021)
Rainfall in May (mm)	0.022 (0.029)	0.005 (0.025)
Slope (%)	-0.055 (0.061)	-0.126† (0.071)
ln (real value of household assets)	0.026† (0.015)	0.035* (0.014)
Share of noneducated working-age household members	-0.087** (0.024)	-0.087** (0.023)
Gender of household head (= 1 if female)	-0.481* (0.214)	-0.180 (0.168)
Wave 2 dummy	-0.025 (0.016)	-0.047** (0.015)
Wave 3 dummy	0.008 (0.025)	-0.021 (0.025)
Intercept	Included	Included
No. of observations	5,031	5,031
p-value (H_0: Variables are jointly insignificant)	.000	.000

Source: Author's estimations based on LSMS (various years).

Note: Statistical significance: † 10 percent, * 5 percent, ** 1 percent. EA = enumeration area. As mentioned in the main text, coefficients for agroclimatic similarity are obtained by regressing the predicted fixed effects on time-invariant variables (including an agroclimatic similarity index).

Table A.2 Effects of the adoption of mechanical technologies on the production function and returns on scale

Variable	Adopters		Nonadopters	
Production function coefficients				
ln (Labor use) (person-day per year)	0.649**	(0.217)	0.019	(0.206)
ln (Land) (square meters)	0.327	(0.265)	0.055	(0.121)
ln (Livestock value)	0.000	(0.021)	0.025	(0.017)
ln (Agricultural equipment value)	0.067	(0.043)	0.123**	(0.043)
ln (Other expenditures for purchased inputs)	0.160**	(0.051)	0.245**	(0.062)
Agroclimatic similarity (σ)	0.150*	(0.072)	0.292**	(0.067)
Soil bulk density (MT/m^3)	-0.551*	(0.265)	-0.579*	(0.295)
Soil silt component (%)	0.007	(0.085)	0.024	(0.083)
Soil sand component (%)	-0.093	(0.228)	-0.206	(0.191)
Soil acidity (pH)	-0.092	(0.210)	0.004	(0.165)
Soil organic contents (g/kg of soil)	0.036	(0.061)	-0.033	(0.054)
Euclidean distance to ARS (geographic minutes)	-0.013	(0.038)	-0.021	(0.034)
Euclidean distance to nearest river (geographic minutes)	0.020	(0.013)	-0.013	(0.014)
Euclidean distance to dam (geographic minutes)	-0.003	(0.016)	0.022	(0.016)
Rainfall (historical average, long term, mm)	0.214*	(0.098)	0.074	(0.088)
Rainfall (historical standard deviation, mm)	-0.183*	(0.087)	-0.054	(0.067)
Rainfall in April (mm)	-0.004	(0.011)	-0.015	(0.010)
Rainfall in May (mm)	-0.043*	(0.021)	-0.043**	(0.012)
Wind (10-meter height, annual average, m/s)	0.159	(0.143)	-0.220*	(0.103)
Solar radiation (kWh/m^2, annual average)	0.771	(0.619)	0.134	(0.543)
Slope (%)	0.035**	(0.010)	0.041**	(0.009)
Terrain ruggedness (index)	-0.024**	(0.009)	0.005	(0.009)
Age of household head	-0.084*	(0.033)	0.013	(0.030)
Share of noneducated household members	0.023*	(0.011)	0.037**	(0.011)
Wave 2 dummy	0.015†	(0.009)	-0.015	(0.010)
Wave 3 dummy	0.005	(0.012)	-0.021*	(0.010)
Intercept	Included		Included	
No. of observations	1,662		1,718	
p-values				
H_0: Land, labor, and other expenditures jointly exogenous[b]	.000		.000	
H_0: Model is not overidentified[c]	.317		.378	
H_0: Model suffers from weak identification[d]	.002		.082	
H_0: Variables are jointly insignificant	.000		.000	

Source: Authors' estimations based on LSMS (various years).

Note: Statistical significance: † 10 percent, * 5 percent, ** 1 percent. ARS = agricultural research station. Standard errors are adjusted for possible within–enumeration area correlations of idiosyncratic shocks. Standard errors reported do not account for the potential complications of multiple steps involved in the estimations, as in the literature on the inverse probability weighting–based generalized method of moments. [a] Statistical significance is based on the raw standard errors, which do not account for the potential complications of multiple steps involved in the estimations. [b] Endogeneity test is based on Hausman (1978). [c] Based on Hansen's *J*-statistic. [d] Based on the Kleibergen-Paap *rk* Lagrange multiplier test.

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