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Effects of agricultural mechanization on economies of scope in crop production in Nigeria

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ABSTRACT

Agricultural mechanization has often been characterized by scale-effects and increased specialization. Such characterizations, however, fail to explain how mechanization may grow in Africa where production environments are more heterogeneous and diversification of production may help in mitigating risks from increasingly uncertain climatic conditions. Using panel data from farm households and crop-specific production costs in Nigeria, we estimate how the adoption of animal traction or tractors affects the economies of scope (EOS) between rice, non-rice grains, legume/seed crops, and other crops, which are the crop groups that are most widely grown with animal traction or tractors in Nigeria. The results indicate that the adoption of these mechanization technologies is associated with lower EOS between non-rice grains, legume/seed crops, and other crops, but greater EOS between rice and other crops. An increase in EOS for rice is indicated in both primal and dual analytical approaches. Mechanical technologies may raise EOS between crops that are grown in more heterogeneous environments, even though it may lower EOS between crops that are grown in relatively similar environments. To the best of our knowledge, this is the first paper that shows the effects of mechanical technologies on EOS in agriculture in developing countries.

Keywords: economies of scope, primal model, dual model, rice, inverse-probability-weighting, Nigeria

1. BACKGROUND

Agricultural mechanization has often been characterized by scale-effects and increased specialization. In one way, mechanization can allow specialization in the production of fewer crops, because of enhanced returns-to-scale (Takeshima 2017a, 2017b; Takeshima et al. 2018). Such characterizations, however, fail to explain how mechanization may grow in Sub-Saharan Africa (SSA) where production environments are considered more heterogeneous than elsewhere globally, and diversification in production can help in mitigating risks from increasingly uncertain climatic conditions.

Economies of scope (EOS), which refers to the economic benefits of producing multiple types of outputs rather than specializing in producing a particular type of output, is one of the key production characteristics that pertains to the relationship between technological change and agricultural diversification. Heterogeneity in production environments and the prevalence of multiple-cropping has been considered by some as an inhibitor of agricultural transformation, including in SSA (Timmer 1988; Altieri 2002). However, empirical evidence is scarce on how technologies, including mechanization, change EOS in multiple-cropping systems and complement heterogeneity in production environments.

We fill this important knowledge gap by investigating the role of agricultural mechanization (animal traction or tractors) on EOS in multiple-cropping systems in Nigeria. Nigeria is particularly appropriate in assessing this issue because its crop production systems are diverse, even for SSA. Unlike in eastern and southern Africa where maize dominates, maize is only one of many major crops grown in Nigeria. In addition to maize, other grains, such as rice, root crops, including cassava and yams, and leguminous crops, including cowpea, are grown there. For all of these crops, Nigeria is the largest producer in SSA (Alene & Manyong 2007; FAO 2018). These cropping patterns are explained in part by diverse production ecologies with differences in soil quality and access to irrigation across space. Furthermore, unlike countries, like Ethiopia, where the history of agricultural mechanization, like animal traction, is extensive, animal traction in Nigeria only has spread relatively recently over the last few decades. Consequently, its effect on production characteristics, including EOS, may be more pronounced than in the past.

We focus on the EOS between rice and other crops, as well as legume/seed crops[1] and non-rice grains and other crops, because, first, production of these staple crops accounts for a significant share of cultivated area in Nigeria; and, second, intensive tillage appears to be introduced first for these crops (Takeshima et al. 2013). Additionally, demand for these grains and legume/seed crops continue to rise in Nigeria, especially for rice (Gyimah-Brempong et al. 2016), but also for other cereals, like maize, due to population growth, changes in preferences, and increased demand for fodder. Since, as is partly shown in this paper, rice production system tends to be very distinct from other crops due, for example, to water needs and suitable soil characteristics, investigating EOS in the production of both rice and non-rice grains together with legume/seed crops is important.

Our analyses use the Living-Standard Measurement Study – Integrated Survey on Agriculture (LSMS-ISA) panel dataset for Nigeria. Investigating EOS in rice and non-rice grains-legumes/seed crop production in Nigeria is possible with the LSMS-ISA data, because they contain plot-specific inputs usages and outputs, from which information on the production costs for rice and non-rice grains or

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[1] As is defined more in detail later, we focus on a combined category of "legume/seed crops" because, this category both includes crops for which mechanization is mostly applied in Nigeria and constitutes one of the 12 dietary groups used in FAO's classification of food groups – "legumes, nuts, seeds" (FAO 2011).

legume/seed crops can be obtained separately, as is needed in some of the estimation methods. In addition, the panel nature of these LSMS-ISA data allows us to mitigate various endogeneity issues associated with the production decisions of farm households.

Our study contributes to various strands of research literature. It contributes to studies which assess the impact of agricultural mechanization on production characteristics (Takeshima 2017a; Takeshima et al. 2018), or those assessing the linkages between mechanization and cropping systems (Takeshima et al. 2013). Our study also contributes to the literature on production economies, particularly studies assessing the EOS by firms or organizations of distinct types (Baumol et al. 1982; Coelli & Perelman 1996; Coelli & Fleming 2004; Jin et al. 2005; Renner et al. 2014) by extending their methodologies to the case of African agricultural production. Methodologically, our study also contributes to the literature on impact evaluations, particularly by making use of the inverse-probability-weighting (IPW) method (Wooldridge 2007) to assess the impact of agricultural mechanization on EOS.

Our results indicate that mechanization raises EOS between crops or groups of crops that are more distinct in their production environments, e.g., soil types, such as rice, while it may reduce EOS between crops that are relatively less distinct, such as non-rice grains or legume/seed crops. The results for rice hold for both primal and dual analytical approaches to estimating EOS.

Our paper proceeds in the following way. Section 2 briefly describes the linkages between mechanization and EOS. Section 3 describes the agricultural mechanization patterns and relevant policies in Nigeria. Section 4 discusses the methodologies. Section 5 presents the data and descriptive statistics. Section 6 discusses the results, while section 7 concludes.

2. POTENTIAL LINKAGE BETWEEN MECHANIZATION AND ECONOMIES OF SCOPE IN AGRICULTURE

Economies of scope in producing many crops, instead of specializing in a fewer set of crops, can arise through various mechanisms, including mechanization. While our study does not directly test these mechanisms, we describe some to facilitate the interpretation of the empirical results. Mechanization is related to EOS in part because mechanization can also raise returns-to-scale (Takeshima 2017a; Takeshima et al. 2018), which then affects the potential for specialization among crops.[2] As is indicated below, intra-farm heterogeneity in plot characteristics and crop sensitivity to production environments further affect the relationship between mechanization and EOS.

Economies of scope in crop diversification

Economies of scope can arise at the farm household level if the production environment, such as the soil characteristics of farmed plots, is diverse even within the farm household, and, thus, suitable crops vary across plots. In such case, it is more economical to grow different crops depending on their respective suitability to the plots, rather than planting the same crop on all plots. EOS also arise

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[2] With greater returns-to-scale, specializing in the production of specific crops at greater production scale may be more efficient for farm households, rather than producing a more diverse set of crops at lower respective production scales. Note that returns-to-scale (or more broadly economies of scale) and economies of scope are not mutually exclusive. Sometimes economies of scope arise due to economies of scale. For example, economies of scope in producing rice and non-rice crops simultaneously may arise from using one large machine that can prepare plots for both rice and non-rice crops, rather than obtaining separate smaller machines that are specifically used for either rice or non-rice crops, but not both. In this case, economies of scope in the former may be partly due to the economies of scale associated with the large machine. The aforementioned studies so far focused on the returns-to-scale in aggregate production values with all crops combined (Takeshima 2017a) or returns-to-scale in the production of a single crop (maize in Ghana - Takeshima et al. 2018), and not on the potential effects on economies of scope.

if common knowledge or resources can be easily used across multiple crops. For example, if two crops can be grown with similar husbandry practices, they can be grown side-by-side relatively economically, since farmers will not need to incur costs in acquiring new knowledge for growing different sets of crops.

EOS may not materialize if the conditions are the reverse. A production environment can be such that there is sufficient potential for specialization. For example, crop production environments may be relatively homogeneous within the farm of a farming household, and a household can easily expand the production of a specific crop or group of crops. In such cases, the scale effects from specialization may outweigh the benefits from diversification. If production is knowledge intensive, and distinct knowledge is required for different groups of crops, then growing different crops may reduce overall efficiency, even if they are grown on suitable plots, if farmers lack knowledge on some of these crops. Such crop-specific fixed costs may extend beyond knowledge requirements. If, for example, the quality of seed matters significantly, farmers may incur significant transaction costs in obtaining high-quality seeds for multiple crops from trusted sources. Such sources may specialize in handling seed of fewer crops. If such costs are high, it makes sense for farmers to focus on fewer crops and obtain a large quantity of high-quality seed for each crop, instead of obtaining a small quantity of high-quality seed for many crops. There may be other examples of high fixed costs associated with specific crops, which could lower EOS.

Agricultural mechanization and economies of scope

Agricultural mechanization, particularly the use of more power-intensive tillage methods through the use of animal traction or tractors instead of human labor or no tillage, can potentially affect EOS. Economies of scope with rice, for example, can arise through mechanization if, for example, mechanical technologies make rice production on rice-suitable plots viable by reducing the cost of farm power. This potential is further enhanced as the mechanical technologies can partly overcome certain fixed costs, such as knowledge constraints in rice crop husbandry. Using stronger sources of power like animal traction or tractors may enable farmers, for example, to prepare land with sufficient uniformity, while doing so with human power alone may require additional complementary knowledge.[3] Importantly, EOS in this case remains high because, even with mechanical technologies, it may still be costly to specialize in rice production by switching to rice production on all plots due to the high sensitivity of rice to plot characteristics. EOS also arises if the same equipment or mechanized practices can be used for multiple crops, so that growing multiple crops within the same production system is more efficient than establishing separate production systems for each crop. For example, land preparation, such as tillage, is often involved in the cultivation of both rice and non-rice crops.[4] Animal traction or tractors that typically reduce the costs of tillage for both rice and non-rice crops may reduce the overall production costs of such multiple cropping systems more than it reduces the costs in a mono-cropping system.

However, mechanization may also lower economies of scope. This happens if, for example, a crop has low sensitivity to plot characteristics and mechanization effects on specialization dominate. Furthermore, mechanization may be complementary to the crop-specific fixed costs. For example, the benefits of mechanical land preparation for rice may be sensitive to how machines are used and

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[3] Knowledge is often embedded in technologies themselves (Mokyr 2003).

[4] In Nigeria, the optimal timing of land preparation often fall under similar season for multiple crops, as is illustrated by a typical crop calendar in Nigeria (http://www.peaceworkspartners.org/vault/Nigeria/Research/Nigeria%20Statistics/crop_calendar_nigeria.pdf). Mechanization that enable faster land preparation, can allow more intensive land preparation for multiple crops, including rice and non-rice crops.

using the machines in the same way may lead to very different effects for different crops. Mechanization may also raise the returns from high-quality seed and, thus, may raise the optimal level of transactions costs incurred in securing the seed, which ultimately raises the fixed costs of diversification. While some legumes are often used to provide soil nutrients through nitrogen fixation effects (Roy et al 2002; Toomsan et al. 1995), which is complementary to other crops, mechanization may substitute this through more powerful and timely plowing so that nutrients are directly extracted from deep soil or the absorption of chemical fertilizer becomes more efficient (Ohiri & Ezumah 1990). In such cases, the relative benefits of the complementarity of legumes with other crops may decline. Mechanization may also generally lower EOS if these factors dominate.

3. AGRICULTURAL MECHANIZATION AND POLICIES IN NIGERIA – ANIMAL TRACTION AND TRACTORS

Patterns of agricultural mechanization growth in Nigeria

Agricultural mechanization growth in Nigeria over the past several decades has been characterized by a significant spread of animal traction, but with stagnation in tractor use (Table 3.1). Tractors were promoted in the 1970s and early 1980s as part of the promotion of large-scale farming (Takeshima & Lawal 2018). The share of areas cultivated with tractors has since stagnated at less than 10 percent for several decades. In the meantime, available information indicates that the share of areas cultivated nationwide with animal traction has grown from between 3 to 5 percent in the 1980s to 32 percent in the 2010s, excluding large-scale agricultural enterprises, which are not covered by the LSMS-ISA surveys. In northern Nigeria, the share of land on which animal traction is used has grown from between 6 and 10 percent in the 1980s to 66 percent in the 2010s, excluding large-scale agricultural enterprises. The use of animal traction has been largely limited in southern Nigeria, however, due to Trypanosomiasis carried by tsetse flies (Alsan 2015; Diao et al. 2016) (Figure 3.1). Combined with tractor use, about 38 percent of the farmed area in Nigeria and 68 percent of that in northern Nigeria is cultivated with animal traction or tractors, excluding large-scale agricultural enterprises.

Table 3.1. Levels of tractor and animal traction use over time in Nigeria, excluding large-scale agricultural enterprises

Variables	1960s	1970s	1980s	1990s	2000s	2010s
Arable land (million ha)	28	26	23	32	35	34
Percent of area mechanized						
Tractors	1[b]	5 [b]	9	10	9	10
Animal traction			3 ~ 5 [c]			32
Animal traction in northern Nigeria [a]			6 ~ 10			66
Animal traction or tractors						38
Animal traction or tractors in northern Nigeria						68

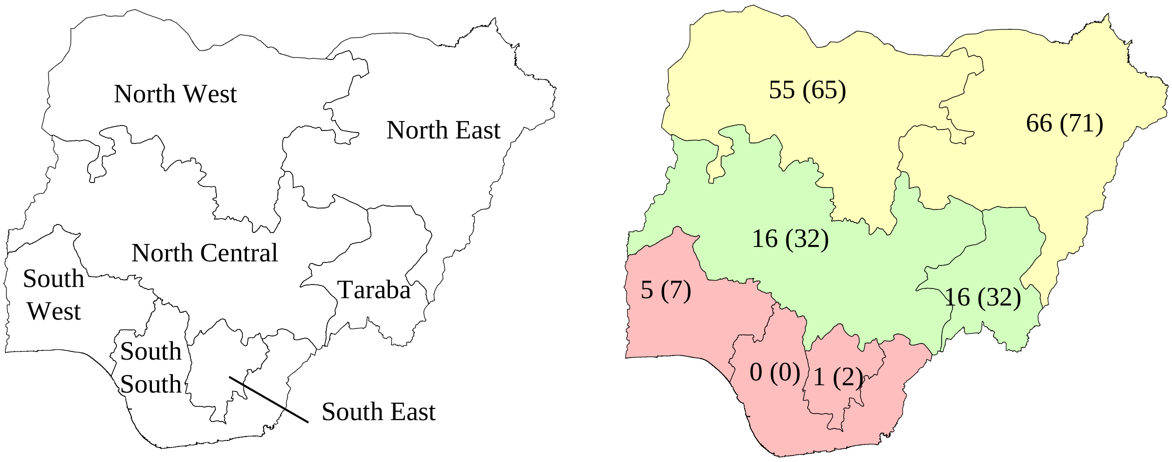
Source: Share of mechanized area by tractors - Dunham (1980), Ugwuishiwu & Onwualu. (2009), Azogu (2009); share of mechanized area by animal traction - Dunham (1980), Philipps et al. (1986), Jansen (1993), and LSMS-ISA. Arable land – FAO (2018).

[a] Northern Nigeria = North West and North East zones, excluding Taraba state.

[b] Extrapolated by authors using the number of tractors in use and arable land from FAO (2018) and the figures for the 1980s by Dunham (1980).

[c] The proportions in 2010s are applied, using the fact that animal traction use in the South has been almost nonexistent.

Figure 3.1. Regions of Nigeria (left); and respective adoption rates of animal traction and tractors, percent (right)



Source: Author's based on the LSMS-ISA survey.
Note: Adoption rates are average of 2010, 2012 and 2015. Figures in parentheses in right map are adoption rates weighted by cultivated areas.

Mechanization-related government programs

Nigeria currently does not have a standalone agricultural mechanization policy, although the envisaged roles of mechanization are specified as part of the country's overall agriculture and nutrition security policy (FMARD 2017). In addition, agricultural mechanization is supported through various government programs, implemented by the federal government and by state and local governments. For state-specific programs, Hatzenbuehler et al. (2018) provides additional descriptions for Kaduna and Benue states.

Recent programs to promote the use of tractors in farming has included subsidized distributions of tractors to selected beneficiaries, including individual farmers or private-sector managed farm machinery hiring service providers. The focus has gradually shifted from the former to the latter over the years, as it has increasingly been recognized that hiring services more efficiently meet the demand by smallholders for mechanized farming services. The Agricultural Equipment Hiring Enterprise (AEHE) program, which started in 2012, is an example of government efforts to support the establishment of independent tractor rental service providers (Takeshima et al. 2015). The government has also put in place several regulatory measures, including testing and certifying machines and operators (Takeshima & Lawal 2018), although the extent of their enforcement is presently unknown and is likely limited in the informal sector. In addition, national agricultural research organizations, such as the Institute of Agricultural Research in Samaru, conduct research on developing farm machinery, such as tractor-attachments. Information about government programs related to animal traction is generally limited, but the known programs include support for veterinary services and research programs on engineering and ergonomics issues associated with mechanical equipment powered by animal traction and improving livestock breeds for animal traction purposes.

The research focus of this study does not directly provide specific policy prescriptions, but it offers some insights into how mechanization adoption in farming may contribute or constrain government's policy goals in the agricultural sector, especially in terms of the effects on consumption, nutrition, trade, and prices of potential shifts in production patterns.

4. EMPIRICAL METHODS

We assess the impact of mechanization on EOS using the Inverse-Probability Weighting (IPW) method, combined with the estimations of EOS using the IPW-regression adjustments (IPWRA) framework. IPWRA has been increasingly used in the literature to assess the effects of technology adoption on various outcomes, including those of mechanical technologies (Takeshima 2017a; Takeshima et al. 2018). IPWRA is suitable when the outcomes of interest are parameters, rather than single values. IPWRA involves estimating the probability that the farm household adopts mechanical technologies, computing the inverse of the weight, and running the main regressions of interests using this weight (Wooldridge 2007). The main idea behind IPW is as follows: IPW assigns greater weights to adopters whose adoption probabilities are actually low given their observed characteristics and to nonadopters whose adoption probabilities are actually high. Doing so, IPW takes advantage of the fact that these farmers have many counterfactual farmers with whom to compare – for those who have low adoption probability and in fact do not adopt, and for those who have high adoption probability and in fact do adopt.

Estimation of inverse-probability-weights

The probability of adoption of mechanical technologies by a farm household is estimated through a probit regression:

$$Probability\ (M = 1|Z) = \hat{p} = \Phi(Z\eta) = \int_{-\infty}^{Z\gamma} \phi(v)dv \qquad (1)$$

where, M is a binary variable, which takes the value of one if the household adopts mechanization and zero otherwise; Z is a vector of household characteristics and η is a vector of estimated parameters. Estimated probability, $\hat{p}$, is computed as $\Phi(Z\eta)$ in which $\Phi(\cdot)$ is the normal distribution function.

Our data are a panel. We define mechanization adoption (M = 1) as households using mechanization (animal traction or tractors) for at least half of the times they reported farming over the three waves of the LSMS-ISA data. Specifically, M = 1 if a household reports using mechanization in two out of three waves in which it reported being engaged with farming, or one out of one or two waves it reported being engaged with farming. Therefore, M is a defined constant within a household across all panel periods. We define mechanization status M in this way for both theoretical and practical reasons. Theoretically, production characteristic of EOS may evolve in the medium-to-long term, rather than in the short term.[5] Practically, treating M as time-invariant, rather than time-variant, allows us to estimate EOS more reliably using a standard fixed-effects panel method.[6] We use a correlated-random-effects (CRE) model (Mundlak 1978; Chamberlain 1984), where Z consists of the average values of relevant exogenous variables of the household over three waves.

We then calculate the inverse-probability weight, w_i, as:

---

[5] This is similar to the understanding that other production characteristics like returns-to-scale also tend to change in medium- to long- term, rather than in short-term (Basu 2008; Takeshima 2017a). The literature also often define adoption as a long-run equilibrium rather than short-term fluctuations (Feder et al. 1985), which may be more accurately characterized through the frequency of technology use over time.

[6] In other words, if M is time-variant, EOS for the same household must be estimated separately for different periods of time depending on M, which is more complicated.

$$
\begin{aligned}
w_i &= \frac{1}{\hat{p}}\ (for\ adopters) \\
w_i &= \frac{1}{1-\hat{p}}\ (for\ nonadopters).
\end{aligned} \tag{2}
$$

which is time-invariant for the household over the panel period. We then apply w_i for all the subsequent analyses described below.

Estimation of economies of scope using IPW-samples

The literature in production economics proposes both primal and dual approaches to empirically estimate the economies of scope in multiple-outputs production. As is widely known, each approach relies on and is more suitable under different specific assumptions. We, therefore, aim to obtain evidence that is consistent with both approaches to show the robustness of our analytical results.

Primal approach

In primal approaches, EOS can be estimated by use of the concept of input distance function (IDF) (Shepard 1970), which has been applied in many studies, including in Papua New Guinea by Renner et al. (2014) and by Coelli & Fleming (2004), in Botswana by Irz & Thirtle (2004), and in Vietnam by Nguyen (2017), among others. Generally, the estimation proceeds as follows (Coelli & Fleming 2004; Coelli & Perelman 1996; Renner et al. 2014).

Estimation of the IDF, which relates to the level of production efficiency measured as the input-oriented distance from the production frontier, involves identifying how outputs and input uses are associated with this IDF. Specifically, for the case of two outputs,

$$
\begin{aligned}
ln\, D = \alpha_0 + \sum_{j=1}^{2} \alpha_j\, ln\, y_j + \sum_{n=1}^{2} \alpha_j\, ln\, x_n + 0.5 \sum_{j=1}^{2}\sum_{k=1}^{2} \alpha_{jk}\, ln\, y_j\, ln\, y_k \\
+ 0.5 \sum_{n=1}^{2}\sum_{q=1}^{2} \alpha_{nq}\, ln\, x_n\, ln\, x_q + \sum_{n=1}^{2}\sum_{j=1}^{2} \alpha_{nj}\, ln\, x_n\, ln\, y_j + \beta_Z \cdot Z
\end{aligned} \tag{3}
$$

in which the IDF (D) is explained as functions of output of crop group j (y_j), values of inputs n (x_n), and Z (k and q are aliases for j and n). Note both y_j and x_n are measured in monetary values, rather than in physical quantities.

Following Renner et al. (2014), Coelli & Fleming (2004), and Coelli & Perelman (1996), the parameters in (3) can be estimated by (4)

$$
\begin{aligned}
-ln\, x_{0,it} \ = \alpha_0 + \sum_{j=1}^{2} \alpha_j\, ln\, y_{j,it} + \sum_{n=1}^{N} \alpha_n\, ln\, x^*_{n,it} + 0.5 \sum_{j=1}^{2}\sum_{k=1}^{2} \alpha_{jk}\, ln\, y_{j,it}\, ln\, y_{k,it} \\
+ 0.5 \sum_{n=1}^{N}\sum_{p=1}^{N} \alpha_{np}\, ln\, x^*_{n,it}\, ln\, x^*_{p,it} + \sum_{n=1}^{N}\sum_{j=1}^{2} \alpha_{nj}\, ln\, x^*_{n,it}\, ln\, y_{j,it} + \beta_Z \\
\cdot Z_{it} + \delta_i + v_{it} - u_{it}
\end{aligned} \tag{4}
$$

in which $x_{0,it}$ is a reference input, and $x^*_{n,it} = x_{n,it}/x_{0,it}$. δ_i are unobserved, time-invariant individual-fixed effects. The reference input $x_{0,it}$ ideally is the input used by all agents (Coelli & Perelman 1996). In our case, we use land area cultivated by household i in year t. $v_{it} \sim$

$i.i.d.N(0,\sigma_v^2)$ and $u_{it} \sim i.i.d.|N(0,\sigma_u^2)|$. α's and β's are estimated parameters. By setting $-\ln D_{it} = v_{it} - u_{it}$, equation (3), which involves unobserved variable *D,* becomes operationalized in (4) (Coelli & Perelman 1996). Applying Olson et al. (1980), Amsler et al. (2016), equation (4) can be estimated by *corrected ordinary least squares* (COLS), rather than Maximum Likelihood Estimation (MLE), to obtain v_{it} and u_{it}.[7] COLS is suitable for small samples like ours, and also is less susceptible to heteroskedasticity in error terms.

Importantly, in the primal specification, x's are combined inputs used for both commodities, and not disaggregated inputs for specific commodities. This contrasts with the dual model described below, which requires cost information for each group of crops.

From (4), EOS between two crop groups are estimated as:

$$\frac{\partial^2 D}{\partial y_1 \partial y_2} = \frac{\left(\frac{\partial D}{\partial y_1}\right)}{\partial y_2} = \frac{\left(\frac{\partial \ln D}{\partial \ln y_1} \cdot \frac{D}{y_1}\right)}{\partial y_2} = \frac{\left(\frac{\partial \ln D}{\partial \ln y_1} \cdot \frac{D}{y_1}\right)}{\partial \ln y_2} \cdot \frac{1}{y_2} = \alpha_{jk} \cdot \frac{D}{y_1 y_2} \tag{5}$$

Therefore, the sign of α_{jk} essentially indicates the presence (or absence) of EOS. Specifically, in the primal model, $\alpha_{jk} > 0$ indicates economies of scope, while $\alpha_{jk} < 0$ indicates diseconomies of scope (Coelli & Fleming 2004; Coelli & Perelman 1996).

Dual approach

The dual approach follows the methodology of Baumol et al. (1982), which has been extended to the agricultural literature (Jin et al. 2005). A key underlying assumption of the dual approach is that the agent tries to minimize the cost of producing a set production target volume. In our case, this assumes that farmers try to minimize the cost of producing the targeted quantity of outputs, rather than maximizing output given the set level of costs. This assumption may be more reasonable for farmers in Nigeria, since the primary goal of many farmers is to secure sufficient food for home consumption first (safety-first, as in Roy (1952)). While many of them also sell surplus crops to the market, market risks may be still significant, due to price risk, buyer risk, or transactions costs in switching sales locations (Takeshima & Winter-Nelson 2012), among others, and may prefer to sell a relatively fixed amount of outputs.

For the case of two crop groups, the dual approach proceeds as follows (Jin et al. 2005). First, we estimate single crop-group cost functions,

$$\begin{aligned} C_1 &= \alpha_1 + \beta_1 y_1 + \beta_{12} y_1^2 + \beta_{1YA}(y_1 Z) + \beta_{1Z} Z \\ C_2 &= \alpha_2 + \beta_2 y_2 + \beta_{02} y_2^2 + \beta_{2YA}(y_2 Z) + \beta_{2Z} Z \end{aligned} \tag{6}$$

in which the cost of producing crop group *j* (C_j) ($j = 1,2$) is a function of output y_j and its square y_j^2, as well as other exogenous variables Z.

For the analysis here, the dual approach is estimated only for EOS between rice and non-rice crops because it requires crop-specific cost information. In our data, such information is available only for rice in a sufficient sample size (explained later in the data section). C_1 is the production costs for all mono-cropped rice plots the household cultivates, and C_2 is the production costs from plots on which all the other crops except rice are grown.

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[7] Primal method equations (1), (2) and (4) are estimated through STATA's `teffects ipwra` command. In this command, both the probit equation to estimate the weights, and main equations, are estimated jointly through generalized method of moments (GMM), and standard errors are also obtained as Huber-White-robust sandwich standard errors.

We then estimate the multiple-crop-group cost function,

$$C_{12} = \gamma + \delta_1 y_1 + \delta_2 y_2 + \delta_{12}(y_1 y_2) + \delta_{1YZ}(y_1 Z) + \delta_{2YZ}(y_2 Z) + \delta_Z Z \tag{7}$$

in which C_{12} is the sum of C_1 and C_2. $C_{12} = C_1$ for households not growing any other crops. Similarly, $C_{12} = C_2$ for households not growing rice. γ and δ are estimated parameters.

Following Jin et al. (2005), we then calculate sample means of predicted values C_1, C_2, and C_{12}, – $\bar{C}_1$, $\bar{C}_2$ and $\bar{C}_{12}$, respectively – separately for mechanized and non-mechanized sample households. EOS then is calculated separately for the mechanized and non-mechanized samples as

$$SOE_{Dual} = \frac{\bar{C}_{12} - \bar{C}_1 - \bar{C}_2}{\bar{C}_{12}}. \tag{8}$$

In the dual approach, $SOE_{Dual} < 0$ indicates economies of scope, while $SOE_{Dual} > 0$ indicates diseconomies of scope.

We then compare EOS across mechanized and non-mechanized farm households. It must be noted that, as was described above, SOE_{Dual} is calculated based on the IPW-sample, and, thus, a simple comparison between mechanized and nonmechanized farm households suffices to attribute any differences to the adoption of mechanization.

Variables

Outputs, inputs, production cost variables

Output variables y_1, y_2 and y_{12} in the primal model equation (4) are real total values of harvests of crop group j. Similarly, the input variables x_n in equation (4) are the real aggregate values of inputs n used for all household farm production. Given the small sample size, we aggregate inputs into two types, labor and non-labor inputs. Non-labor inputs include fertilizer, seeds, agrochemicals, and payment for all services. If own-resources were used, values were imputed using the local market value of those inputs.

Production cost variables C_1 (as well as C_2, C_{12}) in the dual model (equations (6) and (7)), are constructed *at the household level* by aggregating the following costs: expenditures on animal traction, tractor hiring (imputed costs if owned), expenditures on chemical fertilizer and manure, pesticides, herbicides, transportation costs for chemical fertilizer, and seeds. Costs of seeds are actual expenses if purchased, and imputed costs if used from saved seeds. Labor costs are imputed based on the prevailing farm wages within the community obtained from the community survey. If costs cannot be imputed at community level due to a lack of price observations, further imputations are done using the median values of rural and urban areas in respective geopolitical zones and waves.

The costs of land may or may not be included. This is because the actual costs of land are often difficult to observe. Land rent is often excluded from costs in cost studies, since it is a Ricardian rent (Chavas 2001 p. 267; Chavas 1993). Instead, as is described below, potential costs of land are controlled for by other exogenous variables, including farm size.

Explanatory variables

The set of explanatory variables included are expected to capture important variations in a household's probability of adopting animal traction or tractors, and, hence, by hypothesis, economies of scope.

Agroclimatic conditions include historical averages and standard deviations of rainfall, proximity to the nearest major river, which proxies for hydrological conditions, and various soil characteristics, including bulk density, organic carbon content, cation exchange capacity, and sand and silt composition. In addition to these household-level variables, we also capture intra-household diversity in plot characteristics, measured through the total number of plots, total number of farmer-reported soil types (sandy, clay, mixture of sand and clay, forest soil, loamy, and other), soil quality classifications (good, fair, poor), and slope conditions (flat, slight slope, moderate slope, steep/hilly).

In addition to general rainfall level, rainfall risks have been found to be an important determinant of mechanization in Nigeria (Takeshima & Yamauchi 2012; Takeshima 2015). Similarly, general soil conditions in the locality affect the returns from, and the level of farm power needed for plowing, and returns from tractor ownership, which depend on the demand for hiring service in the locality (Binswanger 1986; Takeshima et al. 2015). Thus, these agroclimatic conditions are also likely to affect EOS through their effects on production functions. As was described above, greater intra-household diversity in plot characteristics may raise the EOS for multiple-cropping, while such diversity may have mixed effects on mechanization adoption.

Household demographics include age, the gender of the household head, as well as the number of household members (adult-male, adult-female, and members under 20 years of age). The share of adult household members receiving formal education is included to account for human capital in the household. Household wealth is captured by the value of livestock, agricultural equipment, and other household assets. These household characteristics proxy for general socio-economic conditions that affect the demand for mechanical technologies. An older household head might have had greater exposure to mechanization promoted in Nigeria and other African countries before the Structural Adjustment Program of the 1980s (Wiemers 2015; Takeshima et al. 2018), but younger household heads may also be more receptive to modern mechanical technologies. Female-headed households may have less exposure or access to mechanical technologies, or extension services, but technological backwardness due to gender disparity can affect EOS in either way. Household wealth affects mechanization decision and EOS through increased liquidity.

Access to market and infrastructure is proxied by the distance to the nearest market (km) and the nearest administrative center (km). These affect general transactions costs for accessing goods and services, including tractor hiring service providers, veterinary services, extension services, or agricultural finance; the potential for market-oriented farming; as well as off-farm and nonfarm income-earning activities. Poor market access also is generally found to raise the importance of crop diversification at farm household level for achieving dietary diversity (Ruel et al. 2018), and thus, households' incentives to obtain EOS. On the other hand, similar incentives for diversification may arise from improved market access (Takeshima & Nagarajan 2012), in which case the effects on EOS is reversed.

The aforementioned market access variables do not reflect regional variations in input prices, and, therefore, key input prices or their proxies are also included. These consist of the price of substitute or complementary inputs, like chemical fertilizer, and agricultural wages (measured as the adult-male wage for land preparation). In addition to the diversity across farm plots described above, the aggregate size of the farm and whether it was obtained through outright purchase or through distribution by the village chief are included to capture the implicit cost of land. The sample share of farmers using irrigation within the corresponding EA is included to capture the potential cost of using irrigation, which reflects the local-level hydrological conditions not captured by more aggregate variables, and local knowledge of irrigation. We also include various variables related to animal traction. They include the opportunity costs of using own animals for traction work, such as the local price of beef, milk, and rental price of draft animals. Uses of animal for traction or for meat or milk production are often inter-related (Lawrence & Pearson 2002) including in West Africa (McIntire et al. 1992; Okoruwa et al. 1996).[8] Similarly, the availability of pasture per head of livestock in the local area is included to account for the general cost of livestock rearing. Furthermore, to capture any other location-specific unobserved heterogeneity in the suitability of animal traction use, we include the sample share of farmers using animal traction, and average sample intensity of animal traction use, respectively, at the enumeration area level.

Again, these variables are likely to affect both the decision to adopt mechanical technologies and EOS. Prices of complementary and substitute inputs affect mechanical technologies depending on the shape of the production function. They also potentially affect EOS in several ways, often through their complex interactions with other household characteristics. For example, when fertilizer prices drop, some farmers who have greater knowledge about root crops, which generally require less fertilizer, may find it economical to start producing cereals. Cereals often require more fertilizer, for which farmers have less knowledge, leading to greater EOS between root crops and cereals. However, in the reverse case, it may become more economical to specialize in cereals, thus lowering EOS with root crops. While our focus is not on analyzing these mechanisms, we account for various potential mechanisms by including these input price variables.

Parsimonious models to avoid multicollinearity

In the dual analyses equations (6) through (8), the inclusion of many interaction terms combined with the small sizes of the rice-production samples are found to lead to considerable multicollinearity. The estimated EOSs in equation (8) are, however, highly robust and stable despite the presence of such multicollinearity. In the results section below, we therefore focus on the interpretations of EOS and effects of mechanization on it, instead of closely interpreting the individual coefficients.

5. DATA AND DESCRIPTIVE STATISTICS

Our primary data are three survey waves from the Nigeria LSMS-ISA dataset, collected jointly by the National Bureau of Statistics and the World Bank. The 5,000 households in the panel survey sample were interviewed over three waves (2010/11, 2012/13, 2015/16). The sample selected for the first wave was nationally representative. The panel sample was selected through stratified random sampling methods. F a total of 500 enumeration areas (EAs), 10 randomly selected households were interviewed in wave 1. These same households were interviewed again in waves 2 and 3.

Our analyses focus on the sub-sample of agricultural households. Further, the estimation of parameters needed for EOS focuses on smaller sub-samples of farmers who grow a particular crop (or group of crops) of interest. Specifically, the estimation of propensity to adopt mechanization is done for 7,326 sample households in total from the three waves. Furthermore, as is described later, our subsequent analyses focus on sub-samples within an area of common support, and thus the sub-samples used in the analysis are further reduced. Specifically, since IPW can be susceptible to propensities ($\hat{p}$) being close to 0 or 1 (Busso et al. 2014), we limit households in the sub-samples for subsequent analyses to those with $0.025 < \hat{p} < 0.975$. This process of excluding households in the off-support sub-sample further reduces the analytical sub-sample size by about half.

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[8] For example, in Asia, the opportunity cost of one day of draft work equals 1 kg of live-weight gain or the production of 4 to 5 liters of milk (Lawrence & Pearson 2002).

In the dual analyses, households growing rice through mixed cropping with other crops on the same plots were also excluded. This is because information of production costs are available at the plot level rather than the crop level, and crop-level production costs C_j for rice only can be computed if rice is the sole crop grown on the plot. This reduces the sample size by about 30 percent. Furthermore, about 10 percent of farmers reported missing values of either farm size or soil quality of the plots. Since farm size is one of the critical variables, these observations were also excluded in the analysis.

Altogether, the primal and dual analyses for EOS between rice and non-rice crops focus on about 3,000 observations in common-support, as well as about 400 observations of rice production costs, and 350 observations of joint production costs for both rice and non-rice crops.

LSMS-ISA data are then complemented by various agro-climatic data. Historical rainfall data and their standard deviations between 1980 and 2010 were obtained from the Climatic Research Unit of the University of East Anglia (CRU 2017). The Euclidean distance to the nearest major river from a corresponding EA is calculated from Lehner et al. (2006). The Euclidean distance to the nearest major agricultural research station (ARS) is from Takeshima & Nasir (2017). The data on various aspects of soil are taken from soil mapping data at 1-km resolution (ISRIC 2013; Hengl et al. 2014). Spatial data of pasture area is obtained from Ramankutty et al. (2008).

Based on LSMS-ISA data, we define non-rice grain as the combination of sorghum, maize, millet, acha (*Digitaria exilis* or *D. iburua*), and wheat. Legume/seed crops are defined as the combination of cowpea, groundnut, bambara nut, sesame, pigeonpea, pumpkin seed, soybeans, *zobo* (hibiscus) seed, and *agbono* (*Irvingia gabonensis*).[9]

All monetary values are expressed as real values through deflation by the local average prices of the main staple crops, which are rice and gari (processed cassava), as calculated by the prices reported by the community survey data included in the LSMS-ISA dataset.

Mechanization and crop choices

Table 5.1 summarizes the proportions of reported farm plots from the combined three waves of LSMS-ISA data in which rice, non-rice grains, legumes, and all the other crops are grown, as well as the share of each type of plots where mechanization (either animal traction or tractors) was used.

Table 5.1. Distributions of crop choices and mechanization use at the plot level

		% of plots in which these crops were grown and mechanical technologies were used		
Crop groups	**% of plots grown[a]**	**Either animal traction or tractors**	**Animal traction**	**Tractor**
Rice	4	44	30	14
Non-rice grains	52	37	34	3
Legume/seed crops	29	46	43	3
Other crops	51	6	4	2

Source: Authors, based on three waves of LSMS-ISA data combined.
[a] Sum of the figures on this column exceeds 100 because multiple crop groups may be grown on the same plots.

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[9] As mentioned above, our focus on combined group of legume/seed crops is motivated by FAO's (2011) dietary diversity classification. We, however, excluded tree nuts, which are also included in FAO's dietary group classifications, because application of mechanization for tree nuts differ considerably from those of field crops. Tree nuts are instead included in "other crops". In addition, other "seeds" that are explicitly included in LSMS-ISA's crop-code, including "seed cotton" and "cotton seed", are also excluded, because they are classified under "oils and fats" by the FAO.

Table 5.2 provides information on use of mechanization across crop groups among farmers growing rice, non-rice grains, and legume/seed crops, respectively, and their use on all the other respective crops. Among the farmers in the analytical sample, mechanization is used across crop groups, if it is used at all. This indicates patterns consistent with the discussion in section 2 that animal traction or tractors can be used across more than one crop.

Table 5.2. Use of mechanization among farmers growing both crop groups

Categories		Mechanize other crops	
		No	Yes
Mechanize rice	No	49.2	7.8
	Yes	2.1	41.0***
Mechanize non-rice grains	No	64.6	0.9
	Yes	0.9	33.7***
Mechanize legumes/ seeds	No	55.2	1.0
	Yes	0.6	43.2***

Source: Authors' calculations based on LSMS-ISA data. Asterisks indicate the statistical significance based on chi-square test: *** 1%.

Table 5.3 provides indicators of plot heterogeneity of production associated with rice, non-rice grains, and legume/seed crops, with respect to other crops grown by the same households. Clearly, rice is grown on distinct plots. In only 30 percent of rice-grown plots are other crops also grown, indicating that rice is predominantly sole-cropped. This is consistent with the hypothesis that the characteristics of plots suitable for rice production are quite different from plots suitable for other crops. In contrast, among plots where non-rice grains or legume/seed crops are grown, 70 to 80 percent of them are also cultivated with other crops. Similarly, 33 percent of rice growers report growing other crops on plots with different soil types than are found on their rice plots. This proportion is only 10 to 12 percent for non-rice grains or legume/seed crops. Similar differences also hold for plot slope characteristics. Overall, these patterns are consistent with the hypothesis that rice is grown in distinctly different production environments from other crops, while non-rice grains or legume/seed crops are grown in relatively similar production environments with other crops.

Table 5.3. Indicators of plot heterogeneity of production for rice, non-rice grains, and legume/seed crops

Crop groups	% with other crop groups grown on the same plot	% with other crop groups grown on the plots with the different reported characteristics within the household		
		soil type	soil quality	slope
Rice	30	33	7	22
Non-rice grains	73	12	5	12
Legume/seed crops	84	10	6	12

Source: Authors' calculations based on LSMS-ISA data.

Descriptive statistics

Table 5.4 summarizes the calculated household level production values and production costs of rice and non-rice grains, legume/seed crops from all plots defined above. It also separately reports figures among "specializers", who produce either rice or non-rice grains and legume/seed crops (combined) but not both, and "diversifiers", who produce both rice and non-rice grains as well as legume/seed crops. We will primarily use these figures and sample for the dual analyses. Similarly, Table 5.5 summarizes the output values for other crops and inputs values for all production combined, which are used for the primal analyses.

Table 5.4. Production costs and output values of rice, non-rice grains, and legume/seed crops at household level, real value equivalent in kg of staple crops

Types	Crop groups	Variables	Sample size	Percentile				
				5%	25%	50%	75%	95%
Specializers	Rice	Output value (y_1)	53	255	683	1091	1,820	5,210
		Cost (C_1)	53	83	135	255	813	7,407
	Non-rice	Output value (y_2)	6,133	31	240	695	1,560	4,554
		Cost (C_2)	6,133	68	345	914	2,006	6,389
Diversifiers	Rice	Output value (y_1)	504	31	209	394	789	2,086
		Cost (C_1)	504	13	50	130	242	1,095
	Non-rice	Output value (y_2)	504	107	426	919	1,818	4,855
		Cost (C_2)	504	117	389	922	2,162	6,683
	Combined	Output value ($y_1 + y_2$)	504	278	773	1545	2,753	6,595
		Cost (C_{12})	504	167	538	1122	2,508	7,498

Source: Authors' calculations based on LSMS-ISA data.

Table 5.5. Outputs and inputs values, real value equivalent in kg of staple crops

Variables	Sample size	Percentile				
		5%	25%	50%	75%	95%
Output – rice	557	35	218	449	952	2,631
Output – non-rice grains	4,762	15	177	480	1,028	2,671
Output – legume/seed crops	2,965	15	90	239	525	1,851
Output – total	7,326	33	268	748	1,663	4,760
Input – labor	7,326	8	164	557	1,456	5,289
Input – non-labor expenses	7,326	0	33	148	451	1,763

Source: Authors' calculations based on LSMS-ISA data.

Importantly, among diversifiers, resource uses for rice (measured in C_1) are relatively small compared to resource uses for non-rice (C_2), with the median of 130 versus 922 kg of staple crops, respectively. This suggests that, among diversifier rice-farmers, resource uses for rice can be significantly affected by resource uses for non-rice crops.

Other explanatory variables

Table 5.6 presents the balancing properties of the IPW-samples in terms of sample means and standardized differences.[10] Statistical significance indicates the differences in the mean values of each variable. Comparison of raw sample and IPW sample indicates that the IPW process significantly reduces the differences in sample averages between the two groups of farmers. Furthermore, the standardized differences in each variable are also significantly reduced in the IPW sample to the order of 0.1 or less, which suggests sufficient balancing properties (Austin 2009).

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[10] Standardized difference (Flury & Riedwyl 1986) compares the differences in means in units of the pooled standard deviation. It is a measurement that is not influenced by sample size and considered suitable as a supplementary indicator for measuring the balancing properties (Austin 2009).

Table 5.6. Descriptive statistics, rice versus other crops

	Raw sample			IPW sample		Standardized differences[a]	
	Non-mechanized	Mechanized		Non-mechanized	Mechanized	Raw sample	IPW sample
EA sample share of mechanizers	0.287	0.633	***	0.476	0.485	0.867	-0.052
Price-of-beef (ln, real value per kg)	2.023	2.072	***	2.038	2.028	0.248	0.107
Price-of-milk, ln(real value per kg)	0.442	0.392	***	0.416	0.416	0.021	0.080
Agricultural-capital, ln(real value)	1.719	1.814	**	1.741	1.723	0.086	-0.031
Livestock, ln(real value)	3.893	5.098	***	4.361	4.075	-0.079	0.053
Pasture area per head of livestock, index	0.029	0.021	***	0.024	0.022	-0.091	-0.023
Local average animal traction use intensity, days	2.47	6.49	***	4.45	4.69	0.522	-0.113
Animal traction rental cost per day, real value	33.62	39.81	***	36.89	37.29	-0.115	0.082
Household size – adult male, ln	0.072	0.157	***	0.148	0.125	-0.019	-0.033
Household size – adult female, ln	0.150	0.199	†	0.206	0.201	0.090	0.026
Household size – children, ln	0.769	0.989	***	0.948	0.977	0.126	0.061
Household head is female, 0/1	0.052	0.023	***	0.041	0.032	0.032	0.022
Age of household head, years	48.5	48.1		48.1	48.3	-0.062	0.113
Distance to the nearest market, km	78.3	72.9	***	77.6	77.6	-0.196	0.040
Distance to nearest administrative center, km	90.9	90.6		85.9	85.0	-0.038	-0.116
Farm size, outright purchase, ha	0.165	0.115		0.147	0.106	0.152	0.000
Farm size, community distributed, ha	0.883	0.772		0.732	0.693	-0.081	-0.018
Real fertilizer price, ln(real value per kg)	0.014	0.036		0.058	0.023	0.031	0.000
Real farm wage, ln(real value per day)	1.724	1.667	***	1.692	1.703	-0.136	-0.025
Non-farm household assets, real value, in ‘000s	1.470	1.439		1.468	1.476	0.200	0.044
Share of non-educated working-age members	0.417	0.474	***	0.456	0.449	-0.053	0.028
Local sample share of irrigators	0.060	0.057		0.065	0.059	0.257	0.007
Plots cultivated, number	2.149	1.817	***	1.949	1.955	-0.134	-0.091
Soil types at farm household level, number	1.170	1.152		1.157	1.132	0.094	-0.034
Soil qualities at farm household level, number	1.045	1.041		1.034	1.034	-0.007	-0.094
Slope categories at farm household level, number	1.169	1.131	***	1.142	1.133	0.087	0.002
Soil bulk density, mt/m^3	1.340	1.385	***	1.371	1.369	0.265	0.163
Soil silt composition, %	19.62	20.44	***	20.305	19.723	0.237	0.054
Soil sand composition, %	64.61	65.16	*	64.788	65.360	-0.101	-0.062
Soil acidity, pH	6.195	6.405	***	6.335	6.319	0.129	0.121
Soil organic content, g/kg of soil	8.733	7.189	***	7.721	7.800	-0.351	-0.036
Euclidean distance to ARS, ln(km)	2.319	2.486	***	2.400	2.297	-0.076	0.056
Euclidean distance to major river, ln(km)	0.016	0.017		0.016	0.017	0.114	0.117
Historical rainfall, average, mm	1042.7	889.6	***	946.9	969.3	-0.401	-0.057
Historical rainfall, standard deviation, mm	158.6	151.3	***	154.4	156.0	-0.195	0.071
Rainfall anomaly, principal component 1	0.272	0.815	***	0.555	0.478	0.310	0.012
Rainfall anomaly, principal component 2	-0.630	-0.731	***	-0.709	-0.677	0.001	0.006
North-Central zone dummy,0/1	0.240	0.091	***	0.146	0.185		
North-East zone dummy,0/1	0.234	0.316	***	0.283	0.260	-0.103	0.021
North-West zone dummy,0/1	0.416	0.579	***	0.515	0.480	0.337	0.074
South-East and South-South zone dummy, 0/1	0.037	0.005	***	0.018	0.039	-0.182	0.046
South-West zone dummy, 0/1	0.072	0.008	***	0.037	0.037		
LSMS-ISA survey wave 1, 0/1	0.304	0.311		0.300	0.317		
LSMS-ISA survey wave 2, 0/1	0.330	0.335		0.325	0.322	0.013	0.031
LSMS-ISA survey wave 3, 0/1	0.366	0.353		0.374	0.361	-0.047	0.018

Source: Authors’ calculations based on LSMS-ISA data. Asterisks indicate the statistical significance of the difference between nonmechanized households and mechanized households: *** 1%; ** 5%; * 10%; †15%

[a] Standardized differences are not calculated for variables which were dropped due to perfect collinearity.

[b] ”Real value” equals kg of staple foods (average of local rice and processed cassava) in local market price. “ln” indicates natural-log transformation.

6. RESULTS

The results of primary interest are the effects of mechanization adoptions on economies of scope. We first briefly describe the factors associated with mechanization adoption, and then discuss the results on EOS.

Factors associated with mechanization adoptions

Results of the probit equation (1) indicate that various key factors are associated with farm household's mechanization adoption decisions (Table 6.1). Generally, the adoption of mechanization (animal traction or tractors) is positively associated with spatial factors, including the adoption rates or average intensity of animal traction within the locality (EAs), as tractor service providers or those renting out draft animals often prefer to remain within the locality due to generally low mobility. Greater availability of pasture per livestock may also lower the cost of livestock feeding and encourage the adoption of draft animals. Greater holding values of agricultural capital, livestock, may indicate farmer's ability to use their own assets for mechanization, or, combined with other household assets, indicate greater liquidity to cover the costs of more intensive production practices that are generally adopted together with mechanization.

Table 6.1. First-stage probit to estimate the propensity score of mechanization

Variables	Coefficient		Standard error	Marginal effects on probability [a]
EA sample share of mechanizers	3.052	***	(0.147)	0.610
Price-of-beef	-0.013		(0.154)	-0.003
Price-of-milk	-0.049		(0.091)	-0.010
Agricultural-capital	0.077	***	(0.024)	0.015
Livestock	0.028	***	(0.008)	0.006
Pasture area per head of livestock	1.582	*	(0.811)	0.316
Local average animal traction use intensity	0.068	***	(0.010)	0.014
Animal traction rental cost per day	0.003	**	(0.001)	0.001
Household size – adult male	-0.025		(0.045)	-0.005
Household size – adult female	-0.018		(0.037)	-0.004
Household size – children	-0.029		(0.021)	-0.006
Age of household head	-0.006	**	(0.002)	-0.001
Household head is female	0.330	†	(0.208)	0.066
Distance to the nearest market	-0.002	**	(0.001)	-0.000
Distance to the nearest administrative center	-0.001		(0.001)	0.000
Farm size (outright purchase)	0.000	†	(0.000)	0.001
Farm size (community distributed)	0.000	***	(0.000)	0.001
Real fertilizer price	-0.140	**	(0.067)	-0.028
Real farm wage	0.201		(0.352)	0.040
Non-farm household assets	0.351	***	(0.039)	0.070
Share of non-educated working-age members	-0.049		(0.090)	-0.010
Local sample share of irrigators	0.508	**	(0.210)	0.102
Number of plots cultivated	0.042		(0.039)	0.008
Number of soil types at farm household level	0.191	**	(0.078)	0.038
Number of soil qualities at farm household level	-0.430	***	(0.130)	-0.087
Number of slope level at farm household level	0.079		(0.082)	0.016
Soil bulk density	0.793	†	(0.548)	0.159
Soil silt composition	0.037	**	(0.015)	0.007
Soil sand composition	0.008		(0.011)	0.002
Soil acidity	0.008		(0.094)	0.002

Variables	Coefficient		Standard error	Marginal effects on probability [a]
Soil organic contents	-0.040	*	(0.022)	-0.008
Euclidean distance to ARS	-0.114	***	(0.043)	-0.023
Euclidean distance to major river	3.015		(2.432)	0.603
Historical rainfall (average)	0.000		(0.000)	0.000
Historical rainfall (standard deviations)	-0.003	**	(0.002)	-0.001
Rainfall anomaly (principal component 1)	-0.078	*	(0.044)	-0.016
Rainfall anomaly (principal component 2)	-0.098	†	(0.066)	-0.020
Zone dummy	Included			
Wave dummy	Included			
Sample size	7,326			
p-value (H_0: variables are jointly insignificant)	0.000			

Source: Authors' estimations using LSMS-ISA data. Asterisks indicate statistical significance: *** 1%; ** 5%; * 10%; †15%

[a] Marginal effects are estimated at sample means of all exogenous variables.

The probability of mechanization is also positively associated with households with younger heads, proximity to the nearest market, greater farm size, local prevalence of irrigation, and the proximity to ARS, which are all intuitive. Associations are also positive with having a female household head. This may indicate that, if the households have the same characteristics, including resource endowments, having a female head may actually induce more adoption of mechanization. A higher price of substituting inputs, like chemical fertilizer, is negatively associated with mechanization. This suggests that mechanization adoption may also accompany greater intensification in agricultural production, including greater overall chemical fertilizer use.

While rainfall variability was hypothesized to induce mechanization, negative effects instead are observed. This is possibly because mechanized production and accompanying intensification patterns may be risk-increasing and discourage risk-averse farmers from adoption. Greater soil bulk density is also positively associated, as such soils tends to require greater farm power, consistent with past studies (Takeshima et al. 2015). Greater household-level diversity in soil types and soil qualities are also associated with mechanization adoption, although their combined effects are somewhat unclear. This may be because mechanization adoption may exploit both scale effects from homogeneity and scope effects from heterogeneity, respectively, of production environments. In addition, local level soil characteristics, such as silt composition, and organic contents also affect mechanization adoption decisions.

Effects on economies of scope

The estimated EOS parameters for the production of rice and other crops, among both mechanization adopters and nonadopters are summarized from both the primal analyses (Table 6.2) and the dual analyses (Table 6.3). These estimates are adjusted for IPW, and, therefore, are directly comparable across mechanization adoption status. Full regression results are presented in Appendix Tables A.1, A.2, and A.3. Importantly, the presence of EOS is indicated in opposite ways in the primal and dual analyses, i.e., positive signs in the primal analyses and negative signs in the dual analyses.

Table 6.2. Primal analyses of economies of scope, rice versus other crops

	Raw sample		IPW sample	
Categories	Adopters	Nonadopters	Adopters	Nonadopters
Economies of scope parameter	0.023 (0.026)	0.111*** (0.024)	0.109*** (0.040)	0.010 (0.051)
Sample size	182	237	182	237

Source: Authors' calculations based on LSMS-ISA data. Asterisks indicate the statistical significance: *** 1%
Standard errors, in parentheses, are estimated through paired bootstrap.

Table 6.3. Dual analyses of economies of scope, rice versus other crops

	Raw sample		IPW sample		Sample-selection sample	
Type of analyses	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters
Non-transformed	-0.179** (0.082)	-0.140 (0.129)	-0.261** (0.102)	-0.050 (0.190)	-0.227** (0.101)	-0.169 (0.160)
Box-cox transformation (λ = 0.5)	-0.112 (0.134)	-0.052 (0.165)	$-0.217^{\dagger}$ (0.148)	0.018 (0.165)	-0.209* (0.122)	-0.130 (0.193)
Sample size	195	158	195	158	195	158

Source: Authors' calculations based on LSMS-ISA data. Asterisks indicate the statistical significance: ** 5%; * 10%; †15%
Standard errors, in parentheses, are estimated through paired bootstrap.

Table 6.2 suggests that, based on the primal approach, mechanization adoption significantly increases the EOS between rice and non-rice crop production. Specifically, the results indicate that, while non-mechanized farmers exhibit no EOS, mechanized farmers do. In other words, while there is no economic advantage to diversify production between rice or non-rice crop under non-mechanized farming, there are advantages in diversifying under mechanized conditions.

The estimated effects of mechanization on EOS are also largely consistent when estimated through dual analyses (Table 6.3).[11] Figures are significantly negative for mechanized farmers, which indicates that production costs for producing both rice and non-rice crops are lower than costs from specializing in one of these crop groups (for example, -0.261 indicates a cost reduction of 26.1 percent), while they are not statistically significantly different from zero for non-mechanized farmers. Mechanization thus seems to raise the economies of scope.

We also estimated the dual model applying a Box-Cox transformation, as the cost and production figures used in equations (6) and (7) are fairly skewed, and the results may be partly driven by such skewness. We find that, when using λ = 0.5 so that the cost and production figures are transformed into their square roots, respectively, the results still hold. Generally, the estimated cost-reductions range around 20 percent.

Table 6.2 and Table 6.3 also indicate that accounting for farmers' self-selection to mechanize or not, as we have done, is important in obtaining consistent results. In particular, with the raw sample, the primal analyses in Table 6.2 would indicate the opposite results as above, while the dual analyses in Table 6.3 indicate much weaker qualitative differences in the effects of mechanization on EOS.

Economies of scope among other crop combinations – through the primal approach

The primal approach also allows us to obtain indications of EOS for non-rice grains and legume/seed crops (Table 6.4). For both crop combinations, mechanized production exhibits diseconomies of

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[11] Table 6.3 also reports results addressing additional sample-selections, which is discussed later.

scope, while neither economies nor diseconomies are observed among nonmechanized farmers. Therefore, in contrast to rice, for both non-rice grains and legume/seed crops, mechanization adoption is associated with decrease in economies of scope.

Table 6.4. Primal analyses of economies of scope for different crop combinations

Categories	Legume/seed crops versus other crops		Non-rice grains versus other crops	
	Adopters	Non-adopters	Adopters	Non-adopters
Economies of scope parameter	-0.020* (0.011)	-0.001 (0.011)	-0.010† (0.006)	0.005 (0.006)
Sample size	892	1,041	1,092	1,153

Source: Authors' calculations based on LSMS-ISA data. Asterisks indicate the statistical significance: * 10%; †15%
Standard errors, in parentheses, are estimated through paired bootstrap.

We further assessed, using the same IPW framework, whether these differences in the effects of mechanization on EOS for rice and on EOS for non-rice grain or legume/seed crops lead to significant differences in actual cropping patterns (Table 6.5). Mechanization adoption leads to the increased adoption of rice, as well as increased joint production and rice and other crops. This is consistent with the above findings that mechanization raises EOS between rice and other crops. Similarly, mechanization adoption leads to reduced adoption of legume/seed crop production, while it has no effect on the adoption of grain production. Furthermore, mechanization adoption weakly leads to increased production scale of non-legume/seed crops, or grain crops excluding rice. These patterns are fairly consistent with the hypotheses that, between legume/seed crops, non-rice grains, and other crops, mechanization may lead to more specialization due to the decline in economies of scope.

Table 6.5. Mechanization and probability of growing certain combinations of crops

Crop groups	Rice versus other crops		Legume/seed crops versus other crops		Non-rice grains versus other crops	
	Probability of production (1 = 100%)	ln(production value)	Probability of production (1 = 100%)	ln(production value)	Probability of production (1 = 100%)	ln(production value)
Crop group of interest (rice, legume/seed crops, non-rice grains, in respective columns)	0.040** (0.018)	-0.049 (0.272)	-0.035† (0.023)	-0.042 (0.109)	0.003 (0.008)	0.092† (0.062)
Other crops	-0.009* (0.005)	0.048 (0.057)	-0.013** (0.006)	0.093† (0.059)	-0.015 (0.020)	0.068 (0.076)
Both crop groups	0.027† (0.018)	-0.221 (0.260)	-0.039* (0.023)	0.068 (0.067)	-0.016 (0.021)	0.052 (0.059)

Source: Authors' calculations based on LSMS-ISA data. Asterisks indicate the statistical significance: ** 5%; * 10%; †15%
Standard errors, in parentheses, are estimated through paired bootstrap.

Additional sample selection issues due to crop choice decisions

Each of the estimated equations (4), (6), and (7) focus on samples that grow certain crop-groups and, thus, our estimates may be potentially biased if farmers' self-selection of crop choices are not taken into account. Appropriately accounting for such self-selection of crop choices is, however, challenging due to the lack of suitable instrumental variables. In addition, given the relatively small sample size, formally incorporating mechanisms to address sample-selection issues may lead to significant loss of efficiency in estimates.

Furthermore, biases are such that our results provide more conservative estimates. First, as we saw in Table 6.5, mechanization adoption is *not* negatively associated with the decisions to grow rice and to jointly grow rice and non-rice crops. EOS is likely to be higher (lower) for farmers with higher (lower) probability of growing rice. The average EOS is therefore likely to decline if more farmers grow rice. Therefore, the economies of scope estimated among mechanized farmers are likely to be a lower bound, than the EOS estimates among non-mechanized farmers. A similar argument holds for legume/seed crops and non-rice grains.

Additionally, in the dual analyses, we also estimated a model that partly addresses the sample selection issue. It involves the estimation of a bivariate probit in place of standard probit (1) to jointly estimate the probability of adopting mechanization and rice production and the application of the IPW using the estimated joint probability of both mechanizing and growing rice to estimate the later-stage equations (6) and (7).[12] Their results are shown in the last columns of Table 6.3. They are qualitatively similar to the main results. That is, the EOS between rice and other crops is more statistically significant and stronger among mechanized farmers, than among nonmechanized farmers.

Interpretations of other coefficients

Our primary results are on the estimates of EOS and their differences between mechanized and non-mechanized samples that are IPW-adjusted. Interpretations of individual coefficients in Appendix Tables A.1 through A.3 are of secondary importance. In Appendix Table A.1, positive (negative) coefficients indicate positive (negative) associations with input distance function, or greater (less) savings in inputs used given the output level and thus higher (lower) efficiency. Similarly, positive (negative) coefficients in dual analyses in Appendix Tables A.2 and A.3 indicate positive (negative) associations on the production cost functions.

Note that, as was described above, various parsimonious models are investigated for equations (6) and (7) as they are found to exhibit considerable multicollinearity. In Appendix Tables A.2 and A.3, the equations for the rice cost function and joint cost function only include key production factors; namely, agricultural capital, labor, and land. Similarly, interaction terms with output values (y_1 and / or y_2) include only these three production factors, as well as distance to river, and intra-household diversity in plot characteristics. The estimation of EOS as well as implications on our main messages, are, however, found robust to these multicollinearities.[13]

7. CONCLUSIONS AND POLICY IMPLICATIONS

Despite growing interest in promoting agricultural mechanization in African countries like Nigeria, empirical evidence on the effects of mechanization has been scarce. In particular, if mechanization plays a role in agricultural transformation in Africa, it is likely to have to complement crop diversification, at least in the short term, that is a suitable cropping strategy in Africa's heterogeneous production environments. While past literature often focused on the role of mechanization in exploiting scale effects and promoting specialization, its effects on diversification or economies of scope, has not been investigated. The literature is also generally thin on the technological determinants of economies of scope in African farming.

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[12] The literature proposes similar methods, including nested propensity score (Huber 2014), which incorporates two-separate levels of sample selections. We extend their methods to a more general case of bivariate probit (which drops the assumption of "nesting" structure).

[13] Results are available upon request.

Using panel data on farm households and information on crop-specific production costs, we provide insights into this issue. We find that the effects of agricultural mechanization on economies of scope for adopting farm households vary across crops of interests. Specifically, mechanization raises EOS between rice and other crops, while it lowers EOS between legume/seed crops or non-rice grains and other crops.

These findings shed important light on the potential effects of mechanization on production systems, which has not been widely analyzed in the literature. For farm households, mechanization raises EOS with crops that are more distinct in their preferred production environments, such as rice, while it may reduce EOS with crops that are relatively less distinct, such as non-rice grains or legume/seed crops. While future studies must formally test the exact mechanisms, it appears that mechanization raises EOS between rice and other crops, by making rice production profitable on plots that are more suitable for rice. Oftentimes, mechanization is associated with the decision to start growing rice. EOS also remains because, even with the adoption of mechanization, production of other crops remain more suitable on plots for which rice is not suitable.

For non-rice grains or legumes/seed crops, their production environments are like those of other crops. Combined possibly with increased returns to specialization, mechanization, therefore, seems to lower EOS between non-rice grains or legumes/seed crops with other crops, and induce more specialization into non-rice grains only, legumes/seed crops only, or other crops only.

These findings have certain policy implications. First, more support is needed for research to understand how the adoption of agricultural mechanization potentially affects a range of characteristics of farm production. Agricultural mechanization is adopted mainly to substitute for manual labor. However, mechanical technologies are also different from manual labor. Their adoption often goes beyond simply saving the costs of farm energy used to transforming the overall production characteristics of the farm household. Effects on returns-to-scale have been recognized in the literature, and this study further shows the effects on economies of scope. There are likely to be other important production characteristics that can be significantly changed by agricultural mechanization. Better understanding of such effects is important given that certain modes of mechanical technologies, like animal traction, have spread considerably in northern Nigeria in the last few decades. To the extent that crop diversification affects the dietary diversity of farm households, as is often found the case in rural Africa (Ruel et al. 2018), further research is also needed to better understand the effects of agricultural mechanization on nutritional outcomes, mediate by its effect on EOS.

Second, these findings also inform, for example, extension strategies. For rice, farmers will grow more of it, but will not specialize in it with mechanization. It is important to continue recognizing that a farmer's rice production decision continues to depend on decisions related to non-rice crop production on separate plots and through decisions on the use of resources other than land, such as labor and external inputs. Even with mechanization, rice production may remain atomistic, characterized by small production by many farmers – instead of large production by a few farmers. Targeted support to increase rice production may therefore remain difficult, and thus it remains important to continue focusing on modalities that can exploit the existing informal sector. For example, it remains important to develop improved rice varieties with genetic traits that are robust across production environments, which can then be disseminated through the informal seed sector, rather than providing certified seeds to selected large producers. In contrast, for legume/seed crops or non-rice grains, farmers will more likely specialize in the production of specific crop-groups. Exploiting legume-maize or legume-sorghum intercropping, for example, may become less efficient, which has sometimes been promoted by extension staff. Instead, it becomes more important to identify which crop-groups farmers are specializing in and then provide more in-depth extension advice focusing on those crop-groups. Production and market supply may become more concentrated into larger but fewer producers. It may become more important to identify and monitor their characteristics, their production plans, and the production and marketing shocks they experience in order to better forecast local production levels. In the meantime, it becomes more important to train them to be more informed of market risks for specific crop-groups, because production will become more risk-prone compared to mixed-cropping.

Lastly, methodologically, our analysis contributes to the literature on impact evaluations and economies of scope by combining estimation methodologies in their respective fields. Our analysis also expands on the past literature assessing the effects of agricultural mechanization on farm production characteristics in sub-Saharan Africa.

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APPENDICES OF FULL RESULTS

Appendix Table A.1. Primal analyses – Determinants of input distance function using the fixed effects stochastic frontier method

	Rice versus other crops						Legume/seed crops versus other crops						Non-rice grains versus other crops					
	Mechanization adopters			Non-adopters			Mechanization adopters			Non-adopters			Mechanization adopters			Non-adopters		
y_1	0.259		(0.259)	-0.663	***	(0.197)	0.198	***	(0.073)	-0.052		(0.066)	0.062		(0.059)	0.038		(0.044)
y_2	-0.389	**	(0.192)	0.598	***	(0.220)	0.112	†	(0.073)	0.092		(0.066)	0.340	***	(0.055)	0.042		(0.058)
$x_{non\text{-}labor}$	0.173		(0.162)	0.013		(0.188)	0.041		(0.051)	-0.186	***	(0.052)	0.013		(0.048)	-0.180	***	(0.044)
x_{labor}	-0.172	†	(0.112)	-0.333		(0.384)	0.008		(0.047)	0.020		(0.048)	0.083	**	(0.041)	0.034		(0.048)
$y_1 \times y_1$	-0.032		(0.032)	-0.012		(0.033)	0.001		(0.005)	-0.008		(0.006)	-0.004		(0.005)	0.002		(0.004)
$y_1 \times y_2$	0.109	***	(0.040)	0.010		(0.051)	-0.020	*	(0.011)	-0.001		(0.011)	-0.010	†	(0.007)	0.005		(0.006)
$y_1 \times x_{non\text{-}labor}$	-0.093	***	(0.026)	0.126	***	(0.036)	-0.021	**	(0.009)	0.019	**	(0.008)	0.002		(0.006)	-0.004		(0.005)
$y_1 \times x_{labor}$	0.001		(0.021)	0.006		(0.025)	0.001		(0.006)	0.003		(0.006)	0.002		(0.005)	-0.015	***	(0.004)
$y_2 \times y_2$	-0.051	***	(0.014)	0.039	**	(0.019)	-0.007		(0.008)	-0.003		(0.007)	-0.014	***	(0.002)	-0.020	***	(0.005)
$Y_2 \times x_{non\text{-}labor}$	0.017		(0.025)	-0.106	***	(0.020)	0.012	*	(0.007)	0.002		(0.006)	-0.006		(0.007)	0.020	***	(0.006)
$Y_2 \times x_{labor}$	0.034	*	(0.019)	-0.105	*	(0.055)	0.000		(0.006)	-0.014	**	(0.006)	-0.014	**	(0.006)	0.002		(0.006)
$x_{non\text{-}labor} \times x_{non\text{-}labor}$	0.024	***	(0.007)	0.019	***	(0.006)	0.005	†	(0.004)	0.005	**	(0.002)	0.005	†	(0.003)	0.008	***	(0.002)
$x_{non\text{-}labor} \times L$	0.030	**	(0.014)	-0.047	***	(0.011)	0.005		(0.003)	0.008	*	(0.004)	0.004		(0.004)	0.009	**	(0.004)
$x_{labor} \times x_{labor}$	-0.014	**	(0.006)	0.083	***	(0.014)	-0.003		(0.002)	0.002		(0.001)	-0.002		(0.002)	0.001		(0.001)
EA sample share of mechanizers	0.072		(0.144)	-0.508	*	(0.265)	0.140	*	(0.075)	-0.435	***	(0.080)	0.003		(0.069)	-0.368	***	(0.073)
Agricultural-capital	-0.011		(0.014)	-0.010		(0.016)	-0.019	**	(0.009)	0.027	***	(0.008)	-0.014	**	(0.006)	0.020	***	(0.007)
Price-of-beef	-0.193	**	(0.096)	0.249	*	(0.138)	-0.073	*	(0.039)	-0.033		(0.039)	-0.080	**	(0.037)	-0.039		(0.039)
Price-of-milk	0.085	*	(0.048)	-0.006		(0.167)	0.062	**	(0.026)	0.126	***	(0.033)	0.105	***	(0.030)	0.122	***	(0.033)
Pasture area per head of livestock	1.780	***	(0.500)	10.366		(1.431)	-0.276	†	(0.183)	-0.420	***	(0.146)	-0.528	**	(0.219)	-0.265	*	(0.139)
Local avg. animal traction use intensity	0.010	†	(0.007)	0.054	**	(0.021)	-0.001		(0.003)	0.029	***	(0.005)	0.001		(0.002)	0.025	***	(0.005)
Livestock	-0.014	**	(0.007)	-0.003		(0.005)	-0.015	***	(0.004)	-0.003		(0.002)	-0.014	***	(0.003)	-0.002		(0.002)
Animal traction rental cost per day	0.000		(0.001)	0.001	*	(0.000)	-0.001		(0.001)	0.000		(0.000)	0.000		(0.000)	0.000	*	(0.000)
Household size – adult male	-0.087	**	(0.043)	-0.175		(0.150)	-0.024		(0.024)	-0.035		(0.027)	-0.033	†	(0.021)	-0.076	***	(0.022)
Household size – adult female	-0.028		(0.021)	-0.090	*	(0.053)	0.000		(0.014)	0.025	†	(0.016)	0.004		(0.015)	0.033	**	(0.016)
Household size – children	-0.006		(0.026)	-0.065	*	(0.039)	0.006		(0.017)	0.017		(0.014)	-0.040	***	(0.012)	0.006		(0.013)

	Rice versus other crops						**Legume/seed crops versus other crops**						**Non-rice grains versus other crops**					
	Mechanization adopters			**Non-adopters**			**Mechanization adopters**			**Non-adopters**			**Mechanization adopters**			**Non-adopters**		
Age of household head	0.000		(0.003)	0.002		(0.003)	0.002		(0.002)	0.002		(0.002)	0.002		(0.002)	0.001		(0.002)
Distance to the nearest market	0.325	***	(0.123)	-0.189	***	(0.026)	0.017	**	(0.007)	-0.107	***	(0.027)	0.006		(0.005)	-0.098	***	(0.023)
Distance to nearest administrative center	0.470	***	(0.146)	0.071		(0.126)	-0.002	**	(0.001)	-0.005	***	(0.001)	-0.002	*	(0.001)	-0.002		(0.002)
Farm size (outright purchase)	0.186	***	(0.071)	-0.315	**	(0.126)	-0.177	***	(0.026)	-0.198	***	(0.021)	0.000	***	(0.000)	0.000	***	(0.000)
Farm size (community distributed)	-0.069	***	(0.010)	-0.135	***	(0.018)	-0.155	***	(0.015)	-0.132	***	(0.011)	0.000	***	(0.000)	0.000	***	(0.000)
Real fertilizer price	0.046		(0.040)	-0.150	***	(0.042)	0.037	**	(0.016)	0.040	***	(0.013)	0.013		(0.014)	0.031	***	(0.011)
Real farm wage	0.320	*	(0.166)	-0.945	**	(0.446)	-0.125		(0.193)	-0.088		(0.146)	0.117		(0.155)	-0.176		(0.130)
Non-farm household assets	-0.049	†	(0.032)	-0.039		(0.029)	-0.008		(0.017)	-0.037	**	(0.017)	-0.015		(0.016)	-0.024	†	(0.015)
Non-educated work-age members, share	-0.304	***	(0.079)	-0.075		(0.116)	0.029		(0.035)	0.031		(0.041)	0.084	**	(0.035)	-0.026		(0.041)
Household head is female	0.201		(0.150)	-10.085	*	(0.640)	0.240		(0.231)	-0.083		(0.222)	0.291	*	(0.162)	-0.241	†	(0.153)
Local sample share of irrigators	-0.070		(0.215)	-0.332		(0.323)	0.104		(0.163)	-0.231	**	(0.110)	0.043		(0.122)	-0.288	***	(0.105)
Number of plots	-0.300	***	(0.040)	-0.099	*	(0.053)	-0.129	***	(0.018)	-0.149	***	(0.017)	-0.117	***	(0.016)	-0.138	***	(0.012)
Rainfall anomaly, principal component 1	-0.001		(0.018)	-0.026		(0.055)	0.009		(0.018)	0.001		(0.013)	0.034	***	(0.013)	0.001		(0.011)
Rainfall anomaly, principal component 2	0.048	†	(0.031)	-0.048		(0.034)	0.060	***	(0.017)	0.073	***	(0.016)	0.013		(0.013)	0.053	***	(0.011)
Wave = 2	-0.039	**	(0.018)	0.012		(0.012)	-0.021		(0.023)	-0.004		(0.017)	-0.025		(0.022)	-0.019		(0.022)
Wave = 3	-0.028	**	(0.014)	-0.002		(0.006)	-0.043	**	(0.019)	-0.009		(0.015)	-0.052	**	(0.023)	-0.033	*	(0.020)
Constant	0.023	*	(0.013)	-0.002		(0.005)	0.024		(0.017)	0.004		(0.012)	0.029	*	(0.015)	0.020		(0.017)
Sample size	182			237			892			1,041			1,092			1,153		

Source: Authors' estimations using LSMS-ISA data. Asterisks indicate the statistical significance: *** 1%; ** 5%; * 10%; †15%

Note: Figures in parentheses are standard errors, which are estimated through Huber/White/robust sandwich estimator. All time-invariant variables are dropped and included in unobservable household fixed-effects.

Appendix Table A.2. Dual analyses – inverse-probability weighted panel fixed effects method for mechanization adopters

Variables	Rice (group 1)			Non-rice (group 2)			Joint		
y_1	-3.070	***	(0.737)				-1.906		(1.441)
y_1 x y_1	0.766	**	(0.333)				0.028	***	(0.007)
y_2				0.008		(0.330)	-0.245		(1.547)
y_2 x y_2				-0.001	**	(0.000)	-0.023	*	(0.012)
y_1 x y_2							0.005		(0.006)
y_1 x own farm area	0.034		(0.120)	0.014		(0.021)	0.276	***	(0.103)
y_1 x household size (aggregate)	2.726	***	(0.645)	0.020		(0.074)	0.542		(0.621)
y_1 x proximity to the major river	0.394	†	(0.271)	3.557		(3.683)	-0.062	**	(0.030)
y_1 x agricultural capital	-0.026		(0.220)	-0.003		(0.020)	0.018		(0.154)
y_1 x number of plots	-0.070		(0.146)	-0.001		(0.039)	-0.147		(0.162)
y_1 x number of soil types reported	0.312		(0.378)	-0.011		(0.092)	0.708	**	(0.312)
y_1 x number of soil qualities reported	-0.719		(0.612)	0.053		(0.264)	0.748		(0.642)
y_1 x number of plot slope types reported	0.298		(0.543)	0.060		(0.119)	-0.156		(0.591)
y_2 x own farm area							-0.127		(0.096)
y_2 x household size (aggregate)							-0.313		(0.673)
y_2 x proximity to the major river							0.082	***	(0.026)
y_2 x agricultural capital							-0.282	†	(0.181)
y_2 x number of plots							0.237		(0.203)
y_2 x number of soil types reported							0.523		(0.385)
y_2 x number of soil qualities reported							-2.065	**	(0.977)
y_2 x number of plot slope types reported							0.780		(0.650)
agricultural capital	0.026		(0.166)	-0.123		(0.787)	5.912	†	(3.860)
household size (aggregate)	-1.229	***	(0.238)				-33.614	†	(21.446)
own farm area	0.121		(0.128)				-0.230		(5.683)
EA sample share of mechanizers				4.987		(3.963)			
Price-of-beef				6.735	**	(3.168)			
Price-of-milk				0.729		(1.814)			
Pasture area per head of livestock				12.742		(14.154)			
Local average animal traction use intensity				0.018		(0.213)			
Livestock				0.402	**	(0.186)			
Animal traction rental cost per day				0.024		(0.017)			
Household size – adult male				0.613		(1.838)			
Household size – adult female				-1.061		(1.176)			
Household size – children				-3.685	***	(1.034)			
Age of household head				0.080		(0.128)			
Distance to the nearest market				0.653		(0.794)			
Distance to the nearest administrative center				-0.045		(0.086)			
Farm size (outright purchase)				0.000		(0.000)			
Farm size (community distributed)				0.000		(0.000)			
Real fertilizer price				0.537		(1.012)			
Real farm wage				10.361	†	(6.509)			
Non-farm household assets				0.353		(1.192)			
Share of non-educated working-age members				4.044	†	(2.633)			
Household head is female				2.075		(7.484)			
Local sample share of irrigators				-3.472		(7.194)			
Number of plots				2.693	*	(1.608)			
Rainfall anomaly – principal component 1	-0.017		(0.155)	0.659		(1.032)	-2.997		(2.380)
Rainfall anomaly – principal component 2	-0.276		(0.107)	0.493		(1.050)	-6.942	**	(2.656)
Wave dummy	Included			Included			Included		
Constant	Included			Included			Included		
Sample size	244			1,644			195		

Source: Authors' estimations using LSMS-ISA data. Statistical significance: *** 1%; ** 5%; * 10%; †15%

Appendix Table A.3. Dual analyses – inverse-probability weighted panel fixed effects method for non-mechanizers (mechanization non-adopters)

Variables	Rice (group 1)			Non-rice (group 2)			Joint		
y_1	-5.363	**	(2.426)				-3.922		(4.900)
y_1 x y_1	0.001		(0.011)				-0.006		(0.019)
y_2				0.159		(0.239)	0.358		(1.741)
y_2 x y_2				-0.0003	***	(0.000)	0.007	**	(0.003)
y_1 x y_2							0.014	†	(0.008)
y_1 x own farm area	0.130		(0.107)	0.001		(0.013)	-0.160		(0.127)
y_1 x household size (aggregate)	0.942	†	(0.570)	-0.010		(0.067)	0.302		(0.460)
y_1 x proximity to the major river	0.440		(0.330)	-4.917	†	(3.133)	-0.229		(0.405)
y_1 x agricultural capital	0.082		(0.146)	-0.001		(0.020)	0.039		(0.260)
y_1 x number of plots	-0.055		(0.084)	0.051	*	(0.030)	-0.026		(0.170)
y_1 x number of soil types reported	1.452	***	(0.442)	-0.167	**	(0.074)	-1.119	**	(0.415)
y_1 x number of soil qualities reported	0.412		(1.591)	0.075		(0.159)	1.159		(1.514)
y_1 x number of plot slope types reported	0.278		(0.736)	0.145		(0.106)	-0.615		(0.829)
y_2 x own farm area							-0.032		(0.211)
y_2 x household size (aggregate)							-0.586		(0.954)
y_2 x proximity to the major river							1.139	*	(0.640)
y_2 x agricultural capital							-0.245		(0.377)
y_2 x number of plots							0.031		(0.306)
y_2 x number of soil types reported							1.875	**	(0.805)
y_2 x number of soil qualities reported							-1.754		(3.437)
y_2 x number of plot slope types reported							0.906		(1.399)
agricultural capital	-2.365		(3.137)	0.690		(0.654)	6.045		(7.498)
household size (aggregate)	-34.251		(23.643)				-31.795		(42.087)
own farm area	-2.900		(3.148)				5.892		(6.051)
EA sample share of mechanizers				8.802	**	(4.150)			
Price-of-beef				4.204	†	(2.596)			
Price-of-milk				1.955	†	(1.250)			
Pasture area per head of livestock				42.796	***	(11.061)			
Local average animal traction use intensity				0.317	†	(0.203)			
Livestock				-0.036		(0.147)			
Animal traction rental cost per day				0.012		(0.017)			
Household size – adult male				1.392		(1.720)			
Household size – adult female				-0.157		(0.993)			
Household size – children				0.058		(0.716)			
Age of household head				0.091		(0.111)			
Distance to the nearest market				0.894		(0.679)			
Distance to the nearest administrative center				-0.186	*	(0.111)			
Farm size (outright purchase)				-0.153		(0.433)			
Farm size (community distributed)				-0.087		(0.510)			
Real fertilizer price				1.778	**	(0.825)			
Real farm wage				26.681	***	(7.218)			
Non-farm household assets				-0.100		(0.980)			
Share of non-educated working-age members				0.868		(2.140)			
Household head is female				0.332		(9.134)			
Local sample share of irrigators				12.099	**	(5.942)			
Number of plots				.261		(1.400)			
Rainfall anomaly – principal component 1	1.539		(2.939)	-0.826		(0.993)	2.778		(4.536)
Rainfall anomaly – principal component 2	-0.050		(2.945)	1.236		(0.899)	0.429		(4.544)
Wave dummy	Included			Included			Included		
Constant	Included			Included			Included		
Sample size	177			1,403			158		

Source: Authors' estimations using LSMS-ISA data. statistical significance: *** 1%; ** 5%; * 10%; †15%.

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