Adoption of Multiple Agricultural Technologies and Impact on Productivity in Rural Nigeria - A Plot-Level Analysis

by Akuffo Amankwah

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Abstract

While the adoption of improved agricultural practices is seen as a means of increasing farm-level productivity, smallholder agriculture in Nigeria is characterized by low adoption of improved agricultural technologies, and consequently, low productivity. This paper examines the factors influencing the adoption and intensity thereof of multiple agricultural technologies, and their impact on agricultural productivity using nationally representative plot-level data from rural Nigeria. The multivariate and ordered probit models were employed to estimate the adoption and intensity of adoption respectively, and the instrumental variables approach was used to examine the impact of the technologies on productivity. The results from the multivariate and ordered probit models provide evidence of interdependences between the use of practices at the plot level, and that the factors that determine the initial adoption decisions are not necessarily the same factors that influence the extent of use. Though there is evidence of complementarities and substitutabilities among the use of the technologies, the factors that influence plot-level adoption of alternative technologies also differ. Access to agricultural extension and international remittances, years of education and off-farm activities of the manager, and the use of animal traction influence the use of improved seeds and inorganic fertilizer. The use of organic fertilizer and legume intercropping are enhanced by high nutrient availability constraints, low greenness index, and use of animal traction. The intensity of use of the practices are influenced by gender, wage and off-farm activities of the plot manager, and access to agricultural extension services. On the productivity side, improved seeds and inorganic fertilizer are positively correlated with plot-level productivity, while the use of inorganic fertilizer and legume intercropping seems to impact productivity negatively.

Key words: Rural Nigeria, multiple technologies, productivity, multivariate probit, plot level

JEL classification: Q01, Q12, Q16, Q18

1. Introduction

Agriculture continues to be the main source of livelihood of the rural poor in Sub-Saharan Africa (SSA). Increasing agricultural productivity has long been touted as the main avenue to lifting the rural poor out of poverty and ensuring their sustainable development. Agricultural production can be increase by either expanding the area under cultivation and or the use of productivity enhancing sustainable practices. Over the years, however, the rise in agricultural production in SSA has emanated mainly from expansion of area under cultivation, with less adoption of improved and sustainable practices (IFAD 2011). Urbanization and increasing population are, however, causing the conversion of historically agricultural lands into residential. Continuous cropping and land degradation have become rampant, leading to decreased soil fertility and subsequently, low yields. Variations in climatic conditions – rising temperatures, low and erratic rainfall – continue to pose threats to agriculture production, given that agriculture in the sub-region is mainly rainfed.

While the agriculture sector contributed about 22 percent to Nigeria's total GDP in first quarter of 2021, about 70 percent of the country's population were engaged in the agriculture sector mainly at a subsistence level (FAO 2020). According to the 2020 poverty report by the National Bureau of Statistics (NBS), the share of the poor in the country (those living below the poverty line of 137,430 Naira (USD 382)[1] stands at 40.1 percent. The rural and urban poverty rates are 52.1 and 18 percent respectively (NBS 2020). For the rural poor in Nigeria, agriculture is the main source of food and livelihood. Thus, ending poverty among the rural poor in Nigeria requires targeting the agriculture sector, including increasing productivity, enhancing access to input, output and credit markets.

Smallholder farming households in Nigeria, however, face a number of supply and demand side challenges, notably poor land tenure system, very low level of irrigation development, limited adoption of research on agricultural technologies, high cost of farm inputs, poor access to markets and high postharvest losses and waste.[2] These are further compounded by the negative impacts of changing climate in terms of high temperatures and low and unpredictable rainfall patterns, given that the agriculture sector in Nigeria is mainly rainfed. The consequence is low agricultural productivity and food insecurity. Increasing agricultural productivity therefore requires

[1] Using September 2019 exchange rate of 360 Naira to USD1.00 from www.oanda.com
[2] FAO website accessed October 12, 2020. http://www.fao.org/nigeria/fao-in-nigeria/nigeria-at-a-glance/en/

surmounting these challenges at the plot level, including the adoption of improved technologies and sustainable agricultural practices (SAP) (Teklewold 2013).

There are considerable number of theoretical and empirical studies on the adoption of agricultural and sustainable practices (Feder et al 1895; Nkonya et al 1997; Dorfman 1996; El-Shater et al 2016); There are equally a few recent studies in this area focusing specifically on Nigeria (Awotide et al 2016; Liverpool-Tasie et al 2017; Balana and Oyeyemi 2020; Oyetunde-Osman et al 2021). For instance, Balana and Oyeyemi (2020) examines the impact of credit accessibility on the adoption of purchased inputs (improved seeds, inorganic fertilizer, machinery and pesticides). Similarly, Oyetunde-Osman et al 2021 examines the determinants of adoption of agricultural technologies at the household level, without reference to plot-level and productivity implications of adoption. Further, to the best of the author's knowledge, there is no study examining the joint adoption of sustainable agricultural practices at the plot level using nationally representative, geo-referenced data in rural Nigeria.

The paper makes contribution to the growing literature on agricultural technology adoption and productivity in the following respect. First, this study uses nationally representative geo-referenced data to rigorously examine the plot-level adoption of sustainable agricultural practices (improved seeds, organic, inorganic fertilizer, and legume intercropping,) in rural Nigeria. Second, the study contributes to the literature by examining the determinants of adoption and intensity thereof of multiple SAPs at the plot-level, employing estimation strategies that allow for interrelationships between the underlying technologies and farmers choosing a mix of practices (Teklewold et al 2013; Asfaw et al 2016) Third, the paper expands the literature on the impact of SAPs on households by examining the linkage between these technologies and plot-level productivity, while taking into account potential endogeneity. Finally, the paper contributes to the literature by focusing explicitly on the impact of long-term climate variability on adoption and intensity thereof, and their implications for plot-level productivity.

The rest of the paper is structured as follows. In Section 2, description of the data and summary statistics are provided. Section 3 provides the empirical methodology and estimation procedures employed in the study. Section 4 presents the empirical results, and in Section 5 conclusions and policy implications of the study are provided.

2. Data and Descriptive Statistics

2.1 *Data*

The paper uses data from the fourth wave of the Nigeria General Household Survey – Panel (GHS-Panel), conducted by the National Bureau of Statistics (NBS), covering the 2018/19 agricultural season. The GHS-Panel involves 2 visit – post-planting and post-harvest – scheduled to coincide with the main agricultural season in the country. The GHS-Panel is part of the Living Standards Measurement Study – Integrated Survey on Agriculture (LSMS-ISA) project of the World Bank, and thus, the LSMS team provided technical assistance while the Bill and Melinda Gates foundation provided funding for the survey. The LSMS-ISA project in Nigeria has supported the collection of four waves of the GHS-Panel since its inception in 2010. The GHS-Panel has rich information on agriculture and other important indicators. The survey follows a two-stage cluster sampling procedure and is representative at the national and zonal levels with rural/urban stratification. The present study focuses on the rural sector, where crop farming is the main income generating activity of smallholder households.

The GHS-Panel 2018/19 data contains 5,025 households, of which 4,976 households were successfully interviewed with complete information. Of the 4,976 households with complete information, 3,384 are located in rural areas, while the remaining 1,592 are located in urban areas. Of the 3,384 rural households, 2,763 engaged in crop farming and provided plot-level input and output information for the 2018/19 agricultural season. Thus, the analysis and results presented in this paper uses plot-level information from the 2,763 rural farming households. Overall, 7,484 plots are included in the analysis. All plots cultivated and harvested by the household are included, irrespective of the crops planted on them.

2.2 Description of Variables and Summary Statistics

The GHS-Panel 2018/19 has rich plot-level information on several sustainable agricultural technologies. The current study focuses on improved seeds, inorganic fertilizer, organic fertilizer, and legume intercropping. We examine whether farming households in rural Nigeria adopt these technologies as a package or they adopt different bundles on their cultivated plots. A multivariate probit modeling framework is implemented to identify the determinants of adoption of the individual technologies, while examining the possible interdependence between unobserved covariates and the relationship between adopting the different technologies.

The extent to which each of these technologies are adopted (measured as the number of technologies adopted on a given plot) is also examined using the ordered probit model with Mundlak's random effects approach to allow for controlling for unobserved heterogeneity emanating from the effect of plot-invariant variables (such as education of the plot manager of head of household). The paper further examines the causal impact of technology use on plot-level productivity using conditional mixed process (CMP) estimators by Roodman (2011) and Lewbel (2012).

2.2.1 *Dependent variables*

The dependent variables (technologies) considered in this study are improved seeds, inorganic fertilizer, organic fertilizer, and legume intercropping. Improved seeds include the use of modern high yielding varieties recommended by the Federal Ministry of Agriculture and Rural Development (FMARD), adapted to different agro-ecological zones of the country. Households were asked if the seed they planted on the plot during the growing season was improved, as well as the name and certification status of the seed if improved. Thus, we define a plot as having been planted with improved seed if the household responded yes to the question of if the seed planted is improved. The descriptive result shows that about 5 percent of plots were planted with improved seeds.

In Nigeria, inorganic fertilizer comes in the form of Nitrogen, Phosphorus, Potassium (NPK) and Urea. The paper defines adoption of inorganic fertilizer as one if the household applied NPK and or urea on the plot during the 2018/2019 agricultural season. Overall, households in rural Nigeria applied inorganic fertilizer to 44 percent of their plots during the season. Organic fertilizer comes in the form of animal and plant wastes, commonly manure and or crop residues. Organic fertilizer is a natural source of micro and macro nutrients that are vital for crop productivity. The share of plots that received organic fertilizer is 35 percent. We define adoption of organic fertilizer on plot if the household applied organic fertilizer to the plot during the growing season. Legume intercropping involves planting a cereal (e.g. maize) and legume (e.g. groundnut) on the same plot during the growing season. Households in the survey were not asked directly if they used legume intercropping technology on respective plots but were asked the crops they planted on plot during the season. Using this information, we constructed a variable equal to one if the household intercropped a legume crop with other crop(s) on the plot during the 2018/2019 agricultural season. Thus, a plot is said to have received legume intercropping technology if legume and other crop(s) were planted on respective plot during the growing season. The data shows that about 36 percent of plots were intercropped with legumes

On the impact of the technologies use on productivity, the dependent variable is the monetary value of crop(s) harvested per hectare of the cultivated plot. For a given harvested plot, the survey asks for the value of the crop harvested. This value is then divided by the total hectares of plot size and used as the measure of productivity of that plot. Given that at the time of the survey some plots were yet to be harvested or fully complete harvesting, farmers were asked to estimate how much more (quantity) they expect to harvest. For these plots, the value of crops harvested per hectare of plot cultivated is estimated by multiplying the output harvested of each cultivated crop on plot by the average price of the cultivated crop and dividing by the total hectares of plot size. Productivity is measured in terms of value (Naira per hectare) instead of quantities (kilograms per hectare) because of the difficulty of aggregating different kinds of crops that may grow on the same plot and may have different productivity levels and economic values (Asfaw et al 2016).

2.2.2 Independent variables

Based on economic theory and the adoption literature (Kassie et al 2008; Kassie et al 2013; Teklewood et al 2013; Asfaw et al 2016; Leathers and Smale 1991; Mendola 2007; Nkonya et al 1997; Oyetunde-Usman et al 2021), we include relevant explanatory variables in the adoption and impact equations. The variables range from household level characteristics, credit and information access, land tenure, plot-level technical and managerial factors, to climate related variables. Table 1 provides definitions of the righthand side variables included in the analysis.

3. Econometric Framework and Estimation Strategy

3.1 Conceptual framework

Rural smallholder households in Nigeria adopt a mixture of technologies on their plot, either simultaneously or sequentially. Applying multiple technologies on the same plot may result in complementarity or substitutability, where the adoption of one technology may increase the propensity to adopt another, and vice versa. With multiple technologies available, there is possible interdependence between the unobserved heterogeneity, and thus this interdependence should be taken into account when modelling household adoption decisions involving multiple alternatives. Further, in the presence of multiple technologies, adoption becomes path dependent, where lessons learned from adopting the first technology might influence the adoption of subsequent ones.

Intensity of adoption is equally important when examining the adoption of multiple technologies at the plot level. The factors that affect a households' decision to adopt individual technologies might be different from the factors that determine the extent to which the technologies are applied to the plots. The paper defines intensity of adoption as the number of technologies applied per plot in the growing season. Following Teklewold et al (2013), intensity of adoption is also modeled using pooled random effects ordered probit model, given that there are multiple plots per household in some cases.

3.2 Multivariate probit model specification

Following Dorfman (1996), Kassie et al (2008) and Teklewold (2013), the paper models the adoption of agricultural technologies at the plot level following the random utility framework. The decision to adopt a given technology is embedded in the general theory of random utility maximization. Households adopt improved technology or switch from traditional to an improved practice if the utility derived from the improved type is higher than that of the traditional.

Let U_j denote the benefit that the i^{th} household $(i = 1, 2, \ldots . N)$ derives from using improved technology j $(j = S, F, M, L)$ on plot p $(p = 1, 2, \ldots . P)$ and U_0 denote the benefit if otherwise. Given j agricultural technologies, the i^{th} farm household adopts technology j on plot p if $U_j > U_0$. Define the net benefit of household i using technology j on plot p as Y^*_{ijp} which is explained by several observed (X'_{ip}) and unobserved (e_{ip}) factors and specified as follows:

$Y^*_{ijp} = X'_{ip}\beta_j + e_{ip}$.

such that

$$Y_{ijp} = \begin{cases} 1 & \forall \quad Y^*_{ijp} > 0 \\ 0 & \forall \quad Y^*_{ijp} \leq 0 \end{cases}$$

The error terms in a multivariate probit model follows a multivariate normal distribution since households can adopt multiple technologies on the same plot. The multivariate normal distribution has a zero conditional mean and variance normalized to unity to allow for identifying the parameters (Teklewold et al 2013). The covariance matrix of the error terms in the multivariate probit model is given by:

$$\Omega = \begin{bmatrix} 1 & \rho_{sf} & \rho_{sm} & \rho_{sl} \\ \rho_{fs} & 1 & \rho_{fm} & \rho_{fl} \\ \rho_{ms} & \rho_{mf} & 1 & \rho_{ml} \\ \rho_{ls} & \rho_{lf} & \rho_{lm} & 1 \end{bmatrix}$$

where the off-diagonal elements represent the correlation between the unobserved factors influencing the adoption of alternative technologies. Given the heteroscedastic nature of the error terms in the equations and the intra-household correlation of plot-invariant covariates, the MVP model is estimated following Mundlak (1978) approach by including intra-household means of plot-varying variables such as soil quality, irrigation, slope, among others, in the model.

3.3 Ordered probit model specification

Given that the MVP technique described above is only able to identify the factors influencing the adoption of the technologies, we go further to estimate an ordered probit model to examine the extent to which households adopt the technologies on their plots. Theoretically, the factors that affect the adoption of the practices may differ from the factors that determine the extent of application on their plots. Traditionally, intensity of adoption has been measured using continuous variables (such as area planted to the technology or the quantity of an input applied to a particular area). In the case of multiple technologies applied to a specific plot as a package, it is difficult to quantify the extent of adoption in the traditional sense given that some households adopted the full package (all four technologies) while others adopted part (less than 4) on their plots.

Following D'Souza et al (1993), Wollni et al (2010) and Teklewold et al (2013), the present study defines intensity of adoption as the number of the underlying technologies applied to a specific plot during the growing season. While there are alternative estimators that can be used to estimate the intensity of adoption (Greene 2008), the current study employs the ordered probit model due to the path dependent nature of using multiple technologies on the plot during the growing season. Following Wooldridge (2010), Roodman (2011) and Wollni et al (2010), the plot-level intensity of SAP adoption is determined following a latent variable model:

$$Y_{ip}^{*} = X_{ip}'\beta + e_{ip} \qquad e_{ip}|X_{ip}' \sim Normal(0,1)$$

where $Y_{ip}^{*}$is a latent variable underlying the unobserved measure of the number of technologies adopted on a given plot, β is a Kx1 matrix of covariates and X_{ip}' is as defined above and does not contain a constant. Given the axiom of path dependence, for a low Y_{ip}^{*}, the number of technologies is low, while the number of technologies adopted increase as Y_{ip}^{*} increase further. Further, let $\alpha_1 < \alpha_2 < \alpha_3 < \alpha_4$ define unknown cut points or threshold parameters such that

$$Y_{ip} = \begin{cases} 0 & \forall \quad Y_{ip}^{*} \leq \alpha_1 \\ 1 & \forall \quad \alpha_1 \leq Y_{ip}^{*} \leq \alpha_2 \\ 2 & \forall \quad \alpha_2 < Y_{ip}^{*} \leq \alpha_3 \\ 3 & \forall \quad \alpha_3 < Y_{ip}^{*} \leq \alpha_4 \\ 4 & \forall \quad Y_{ip}^{*} > \alpha_4 \end{cases}$$

This equation is estimated using the Maximum Likelihood estimation procedure

3.4 Estimating the impact on productivity - production function specification

The paper explores further the impact of technology use on agricultural productivity, measured as the value of total crop harvests per hectare during the reference agricultural season. The impact of agricultural technology use on productivity is well established in the literature (REFERENCES). The impact of the j^{th} technology on the productivity is specified as:

$$Q_{jp} = Z_{ip}'\gamma_j + X_{ip}'\beta_j + \varepsilon_{ijp}.$$

where Q_{jp} is the value of output per hectare from plot p, X_{ip}' represent household and plot level technical factors, while Z_{ip}' is a vector of the technologies under consideration. It is obvious that Z_{ip}' is endogenous – differences in factors that affect the choice of technologies might also influence productivity (non-zero correlation between Z_{ip}' and the ε_{ijp}). Thus, the choice of technologies is endogenously rather than exogenously determined in the production function. This gives rise to multiple endogeneity problems given the number of technologies included in the model. This implies that estimating the equation without taking into account this heterogeneity may lead to bias estimates and misleading conclusions. The paper account for this by using the instrumental variables (*ivreg2h*) techniques. The *ivreg2h* procedure works by using the model's data (exogenous variables) to generate additional instruments to instrument the endogenous variables. These model generated instruments are used alongside the externally supplied instruments for the endogenous variables in the model.

The choice of external instruments is critical for the ivreg2h procedure in identifying the adoption equations, as the consistency of the instrumental variable procedure lies in the validity of instruments. The choice of instruments should satisfy two conditions. First, the instruments should be correlated with the endogenous technology variables in the production model. Second, they should be uncorrelated with the unobserved variables (error terms) that may affect agricultural productivity. Following economic theory and empirical literature (Asfaw et al. 2016; Dillon et al. 2015), variability in climate during the growing season (March-July) over the period 1980-2018 were used as instruments. Specifically, coefficients of variation of growing degree days (GDD), rainfall, number of days that the maximum temperature is greater than 34 degree Celsius are used as instruments. In estimating the productivity model, interactions of these variables are also included. While at levels these climate variables might be correlated with productivity (e.g. high rainfall results in increased production, high temperature results in low yields, etc.), using the variability in these factors potentially generates uncertainty about productivity (Asfaw et al. 2016). The validity of these instruments is tested, and the results are presented in section 5 below.

4. Results and Discussions

4.1 Joint, marginal conditional and unconditional adoption probabilities

Table 2 presents the plot-level joint and marginal probabilities of adoption of underlying agricultural technologies in rural Nigeria. The table shows that among the technologies under consideration, inorganic fertilizer is the most used technology at the plot level in rural Nigeria. Specifically, inorganic fertilizer is used as a single technology on about 16 percent of cultivated plots, followed by legume intercropping (7%) and organic fertilizer (4.5%). While inorganic fertilizer is the most used technology at the plot level in rural Nigeria, it was adopted jointly with improved seeds on 0.96 percent of plots and in combination with organic fertilizer, 7.13 percent of plots, and jointly with organic fertilizer and legume intercropping, 12 percent of plots. The adoption of improved varieties at the plot-level is very low. In fact, improved seeds were used as a single technology on 2 percent of plots, in combination with organic fertilizer, 0.43 percent of plots, while jointly with organic and inorganic fertilizer, 0.81 percent of plots.

In order to explore descriptively, the interdependence between the adoption of the technologies, the conditional and unconditional probabilities of adoption were estimated (Table 3). Unconditionally, 5 percent of cultivated plots received improved seeds, while 44 and 36 percent received inorganic fertilizer and legume intercropping respectively. The adoption probability of for instance, inorganic fertilizer, increases from 44 percent to 46 percent if the plot received organic fertilizer, and to 73 percent if the plot received improved seeds and legume intercropping. Surprisingly, the results show complementarity between organic and inorganic fertilizer adoption on plot, as the probability of a plot receiving inorganic fertilizer increases if the plot received organic fertilizer. It is important to assess the stability of these results as other covariates are controlled for. Further, the adoption probability of improved seeds increases from 5 percent to 47 percent if the plot received inorganic fertilizer but reduces to 2 percent if the plot received organic fertilizer and legume intercropping. This suggests that in the presence of multiple technologies, more needs to be done to nudge farmers to adopt improved seeds on their plots.

4.2 Determinants of Plot-Level Agricultural Technology Adoption: MVP Results

The maximum likelihood estimates of the MVP model of the factors affecting the adoption of agricultural technologies at the plot-level in rural Nigeria are presented in tables 4 and 5. The model fits the data reasonably well as the Wald test ($\chi^2(160) = 4645.81, P = 0.000$) of the hypothesis that all regression coefficients in each equation are jointly equal to zero is rejected. Similarly, the likelihood ratio test of the hypothesis that the error terms across equations are not correlated is also rejected ($\chi^2(6) = 1200, P = 0.000$), warranting the MVP model instead of separate single equations probit models.

Except for the correlation between improved seeds and organic fertilizer and legume intercropping, the analysis further shows that the estimated correlations between the various technologies is significantly different from zero, with some positive, while others negative. These indicate that the probability of a plot receiving a particular technology is conditional on the probability of that same plot receiving one of the technologies, supporting the use of MVP. This also shows further the interdependency of households' technology adoption at the plot level. For instance, the positive significant correlation between improved seeds and inorganic fertilizer use means that, the adoption of improved seeds at the plot-level is conditional on that same plot receiving inorganic fertilizer, all things being equal. The results further indicate that the use of inorganic fertilizer is complementary to the use of improved seeds as is the use of organic fertilizer and the use of legume intercropping. The correlation between inorganic fertilizer and organic fertilizer is, unsurprisingly, negative, suggesting that the two inputs are substitutes to each other. the analysis reveals similar results for inorganic fertilizer and legume intercropping.

The MVP model results vary substantially across the equations of the different technologies, indicating the heterogeneous nature of the results, and therefore warrants discussing the results separately. The results presented in Table 4 follows Mundlak's (1978) approach where mean of plot-varying covariates are included in the MVP estimation, due to the repeated plot observations per household. This was done to further control for possible unobserved heterogeneity (correlation between unobservable plot-level in-variant factors and the decision to adopt the technologies). The Wald test result ($\chi^2(20) = 60, P = 0.000$) indicates correlation between plot-varying unobserved covariates and the household's decision to use individual technologies on plot.

The results demonstrate the importance of household characteristics and managerial qualities of the manager as key determinants of adoption of most of the practices. The number of years of education of the main decision maker of plot increases the likelihood of using improved seeds and inorganic fertilizer, but also decreases the propensity of a plot receiving organic fertilizer. Male managed plots are more likely to receive organic fertilizer and legume intercropping, compared to female managed plots. On the other hand, female-managed plots have more likelihood of receiving inorganic fertilizer compared to male-managed plots. The availability of road infrastructure, proxied by the distance from the household's dwelling to main market, negatively affect the use of most of the technologies. Specifically, households residing long distances from main markets are less likely to use legume intercropping, inorganic and organic fertilizer on their plot.

Households with access to extension services during the growing season are more likely to adopt improved seeds and inorganic fertilizer on their plots, indicating the importance of agricultural extension services on improved agricultural practices adoption at the plot level in rural Nigeria. The results corroborate Tambo and Abdoulaye (2012) who found positive significant effect of extension on draught maize tolerant varieties adoption in rural Nigeria. The results also indicate the important role played by household's access to non-agricultural sources of income to the adoption of agricultural technologies on their plots. For instance, households who received international remittances are more likely to adopt improved seeds than those otherwise. Similarly, plots where the manager is engaged in non-farm enterprise are more likely to received improved seeds, organic and inorganic fertilizer. Wage earning plot managers are more likely to apply inorganic fertilizers and intercrop their plots, but less likely to apply organic fertilizers to their plots.

Geographically, we see that households located in the northern part of the country are more likely to adopt legume intercropping on their plots, compared to their counterparts in the south. This is probably because agriculture is most predominant in the northern part of the country, and that land ownership is probably more prevalent in the north. The use of animal traction increases the propensity of a plot receiving organic fertilizers and being intercropped.

The greenness of the location of the household, proxied by the normalized difference vegetation index (NDVI), the probability of the household applying inorganic fertilizer to their plots. Agronomically, the greenness of vegetation denotes fertility, and therefore farmers may not be enthused about investing in soil enhancing technologies if they deem the soil fertile. This result is further corroborated by the nutrient availability constraints variable where households that face higher constraints in terms of nutrient availability are more likely to utilize improved seeds.

In terms of land tenure, households are more likely to implement legume intercropping on owned plots, compared to rented plots. This is not surprising given the nitrogen fixing nature of leguminous crops to soils that will be available for future crop cultivation. Thus, if the plot is rented with no possibility of re-renting for future cultivation by the household, then it would not be a good investment that the household would want to undertake.

The size of the plot significantly increases the probability of adopting inorganic as well as the propensity of a plot receiving legume intercropping. This is not surprising since the impact of land size on agricultural technology adoption has been mixed in the literature. For instance, Kassie et al (2011) found a positive significant effect of farm size on the adoption of improved groundnut varieties in Uganda, while Asfaw et al (2016) found the total number of plots owned (which denotes farm size) decreases households decision to adopt organic fertilizer and modern technologies in Niger. The data also shows that the use of legume intercropping is more likely on plots with good soil quality.

The results show further the importance of climatic variables in the adoption of different SAPs at the plot level. Households in areas with high variability of rainfall are more likely to use legume intercropping and organic fertilizer. Similarly, large variation in growing degree days (GDD) increases the propensity of a household intercropping their plots, while at the same time decreasing the likelihood of the plot receiving organic and inorganic fertilizers. In addition, high variations in number of days that the average maximum temperatures are above 34 degree Celsius during the planting/growing season (March-July) deters farmers from using organic and inorganic fertilizers.

4.3 Intensity of adoption – ordered probit model results

The ordered probit model results of the intensity of agricultural technology adoption are presented in Table 6. The estimation was done using the Mundlak (1978) approach by including mean of plot-varying covariates in the model estimation.[3] The approach also allows for examining the marginal impact of each covariate on the degree of adoption (number of technologies adopted per plot) separately. The Chi-squared statistic of the joint significance of all coefficients in the model is rejected at the one percent significance level ($\chi^2(40) = 2878.95,\ p = 0.000$), indicating that the covariates jointly explain the intensity of adoption of agricultural technologies at the plot level in rural Nigeria.

The results show that wage and non-farm enterprise works increase the intensity of adoption of the technologies. Specifically, farmers who work in a non-farm enterprise are about

[3] The joint test of the mean of plot varying covariates is significantly different from zero, implying a correlation between observed and unobserved heterogeneity, thus warranting Mundlak's procedure. Further, we check for the plausibility of estimating a random effects model by conducting a likelihood ratio test, where the null hypothesis is that the correlation between two successive errors terms of plots belonging to the same household. The test rejects the null hypothesis at the 1 percent level, justifying the estimation of a random effects ordered probit model.

4.4 percent more likely to adopt at least one technology and 2.5 percent more likely to adopt more than two technologies on their plot.[4] Similarly, plots whose managers are engaged in wage work are about 1.9 percent more likely to receive at least one technology. Extension accessibility has a positive and significant effect on the intensity of adoption of agricultural practice in rural Nigeria. If a household receives extension contacts during the growing season, the propensity of adopting more than two technologies on their plot increases by 2.6percent.

Road infrastructure proxied by distance from household's dwelling to main market has a negative significant effect on the intensity of adoption. Households who are distanced from the main market are about 0.5 percent less likely to adopt more than 2 technologies and 0.1 percent more likely to not adopt any of the technologies. Similarly, distance from the plot to homestead has negative significant effect on the adoption intensity. These results corroborate Teklewold et al (2013) who found negative significant effect of distance on the intensity of adoption. Irrigation infrastructure negatively influences adoption intensity in rural Nigeria. Households who irrigate their plots are less likely to adopt more than 2 technologies on their plots. The use of animal traction is positively correlated with the adoption intensity of the technologies. Households who use animal traction are more likely to adopt 2 or more technologies by about 14.4 percent.

Another important geographic variable that has negative significant effect on the intensity of adoption is greenness index. Households located in areas with high longterm average greenness index are more likely to adopt one technology, but less likely to adopt more than one technology. Similarly, households located in the northern part of the country are more likely to adopt at least one technology on their plot compared to their southern counterparts.

The results further reveal the importance of climatic variables on plot-level adoption intensity of agricultural technologies in rural Nigeria. Plots located in areas with high rainfall variability are more likely to receive at two technologies, and less likely to not receive any technology. High variability in growing degree days tends to decrease the intensity of adoption. Similarly, the variability in the number of days where the maximum temperature is above 34 degree Celsius tend to decrease the intensity of use of the technologies on plot.

[4] Note that for the ordered probit, the magnitudes were computed by summing up the marginal effects (ME) of the respective intensities. For instance, the probability of adopting only 1 practice = ME1; probability of adopting 2 practices = ME1 + ME2; probability of adopting more than 2 practices = ME3+ME4+ME5; probability of adopting 2 or more practices = ME2+ ME3+ME4+ME5; and probability of not adopting any practice = ME0

4.4 Impact of technology adoption on productivity

In Table 7, the OLS and *ivreg2h* results of the impact of improved agricultural technology on productivity are presented. Value of crop output is defined as the estimated value (in Naira) of all field crops that the household planted and harvested from respective plot during the 2018/19 agricultural season. The technology variables are binary, taking the value of 1 if the household applied the respective technology on plot, and 0 if otherwise. Results for the two estimators are presented. The OLS estimator provides the impact of the practice on plot productivity, without taking into account potential endogeneity problems . The OLS estimator assumes that the use of these technologies is exogenously determined within the production function. Endogeneity, however, occurs when there is a non-zero correlation between the error term of the production function and other covariates. For instance, there might be unobserved variables that affect agricultural productivity and also determines the adoption of any of the technologies under consideration. The endogeneity test suggests that the technology variables are endogenous in the production function.[5] Thus, using the results from the OLS to explain the impact of the technologies on agricultural productivity will be bias and misleading conclusion. To surmount this, the ivreg2h techniques is employed to correct for the shortcomings of the OLS.

ivreg2h is a Stata program contributed by Baum and Schaffer (2012). The program allows for estimating instrumental variables regression with an option to generate instruments using Lewbel's (2012) method to control for potential endogeneity problems. This technique also allows for the identification of structural parameters in regression models with endogenous or mismeasured regressors in the absence of traditional identifying information such as external instruments or repeated measurements.

This approach of Lewbel's allows for constructing instruments as simple functions of the model's data (exogenous variables). For each regressor, the *ivreg2h* approach creates standard form (centered) variables and used as instruments. These standard, model generated instruments can

[5] The *ivreg2h* provides a C statistic that tests endogeneity of the included instruments. The C statistics is defined as the difference of the Sargan-Hansen statistic of the equation with the smaller set of instruments (valid under both the null and alternative hypotheses) and the equation with the full set of instruments, i.e., including the instruments whose validity is suspect. Under the null hypothesis that both the smaller set of instruments and the additional, suspect instruments are valid, the C statistic is distributed as chi-squared in the number of instruments tested. Rejection of the null hypothesis indicates that the technology variables are endogenous in the productivity model.

either by themselves serve to instrument the endogenous variables or can be combined with the external instruments (in this case climate variables). This approach may be applied when no external instruments are available or can be used to supplement external instruments to improve the efficiency of the IV estimator. Similar to other instrumental variable estimators, the validity of these instruments is tested in the *ivreg2h* following three approaches – under-identification, weak-identification and over-identification.

The under-identification test (an LM test that is distributed as Chi-squared) examines the null hypothesis that the estimating equation is under-identified, meaning that the excluded instruments are relevant (correlated with the endogenous regressors). Weak identification - From the results estimates, "weak identification means that the excluded instruments (in the case of my model, coefficient of rainfall and temperature) are correlated with the endogeous regressors (seed, fert, orga, legu) but only weakly. In the ivreg2h procedure, this is tested using the effective F statistis, as well as the Stock-Yogo critical values. From the F statistics and the critical values of Stock-Yogo, one can determine if the instruments are weak or not. If any of the critical values is greater than the effective F statistics, then we can conclude that the instruments are weak and therefore do not have strong explanatory power on the exogenous variables. The Hansen J statistic is used to conduct the overidentification test. The overidentification test is conducted to ensure that that the instruments are valid instruments, are not correlated with the error term (under the null hypothesis that cor(Z,e)=0), and that the excluded instruments are correctly excluded from the estimated equation. Generally, the J statistics should not be significant, thus assuring validity of the instruments. A rejection casts doubt on the validity of the instruments. Under the null, the test statistic is distributed as chi-square in the number of (L-K) overidentifying restrictions.

Further on, the discussion focuses on the results from the ivreg2h estimation procedure. The instruments validity test results are presented at the bottom of Table 7. While the test results confirm the validity of the chosen instruments, it is important to emphasize that no instrumental variable approach is perfect. Thus, while the results presented below are vital, they should be interpreted and applied with caution.

As expected, the results indicate that the use of improved seeds is positively correlated with agricultural productivity. The use of inorganic fertilizers also significantly increases agricultural productivity, all things being equal. Surprisingly, the use of organic fertilizer, however, makes negative significant contribution to agricultural productivity. This can possibly be attributed to the fact that some organic fertilizers, especially crop residues and animal droppings take longer time to decompose and render their benefit within the short growing season, and the strong positive correlation between inorganic and organic fertilizer discussed earlier under the conditional probabilities. This finding is also consistent with that of Asfaw et al (2016) who found negative correlation between crop residues and agricultural productivity (value of output and net crop income). The adoption of cereal-legume intercropping also shows negative significant effect on the value of crop output, which is quite surprising. One possible explanation for the negative impact of cereal-legume intercropping on productivity is that households might be planting several crops on the same plot, more than the soil fertility conditions of the plot can handle. Moreover, the benefit of adopting legume-cereal technology may not accrue to the household within the same growing season. In addition, there are other factors/variables that are usually important to be implemented along this technology, which the current study might not be considering.

I look further at how agriculture productivity in rural Nigeria is explained by plot-level technical and non-technical factors. Given that smallholder farming in Nigeria is rainfed, we see strong correlations between agricultural productivity and weather variables. As expected, high annual rainfall during the growing season positively and significantly increases the value of output harvested at the plot level, while late onset of the rains during the growing season negatively impacts the plot's productivity, consistent with the findings of Asfaw et al (2016). Further, high greenness during the growing season increases agricultural productivity, but surprisingly, long term greenness of the location of the plot/household seems to negatively affect productivity. This can be explained by the fact that high greenness index might be resulting from continuous cropping, which potentially puts pressure on the soil, rendering it unproductive in the long run.

Soil characteristics in terms of quality, topography, nutrient availability and water retentions are critical in explaining plot productivity. The results show that plots with high nutrient availability constraints are less productive, as does plots with steep slopes. Erosion are generally more prevalent on steep plots, and thus, erosion might wash away the topsoil of steep slope lands and render them less productive. As expected, irrigation and access to agricultural extension services positively impacts plot productivity of crops, though the coefficient of extension is not statistically significant. Distance from the household's dwelling to the nearest main market negatively influences plot productivity, which is not surprising. Distance from the plot to the household's dwelling though negative, is not statistically significant.

On the socio-demographic variables, the results show that plots whose managers have more years of education are less productive, while plots managed by males and have high dependency ratios are more productive. Further, the analysis demonstrates the important role of land tenure and tenure security on enhancing plot-level agricultural productivity. Plots that are owned by the household tend to be more productive, compared to rented and other forms of plot acquisition.

5. Conclusions

Improved agricultural technologies have long been hailed as positive production function shifters, and empirical evidence indicates that the adoption of these technologies depends on a number of household characteristics, plot level technical factors, as well as climate variables. In the presence of multiple technologies, households face the choice of either applying a single technology on their plot or adopt a mixture of them during the growing season. This study aims to unravel the factors that hinder or accelerate the use and intensity of use of agricultural practices at the plot level in rural Nigeria, and also examines the impact of the technologies on crop productivity, while controlling for other potential productivity enhancing variables. The MVP modelling technique was used to identify the factors affecting the adoption of the technologies, while the ordered probit model was used to examine the factors influencing the intensity of adoption. The impact of adoption on plot level crop productivity was examined using the instrumental variables approach.

The results indicate that the application of improved seeds and inorganic fertilizer to plots are positively correlated with crop productivity, while the use of organic fertilizer and legume intercropping tend to be negatively correlated with productivity, which can potentially be attributed to delayed realization of the benefits of these technologies as nutrients from nitrogen-fixing legumes and some organic manures might not be harnessed during the growing season. In addition, soil conditions of plots may not be suitable for legume cultivation. The study also finds the importance of climatic and fertility variables such as nutrient availability constraints, rainfall, delayed onset of the rains during the growing season, coefficient of variation of rainfall, maximum temperature, and growing degree days on plot-level productivity.

The results also reveal complementarities and substitutabilities between the technologies, indicating interdependence of agricultural technology use at the plot-level in rural Nigeria. This implies that technology adoption analysis in the presence of multiple alternatives should take into account these interdependences. However, the factors influencing adoption vary across the underlying technologies, and range from managerial and plot level characteristics, to climatic and soil conditions.

The adoption of improved seeds is facilitated by the years of education of the plot manager, non-farm family business, access to remittances, agricultural extension services, and nutrient availability constraints. The adoption of inorganic fertilizer on the other hand is influenced by the years of education of the plot manager, non-farm family business, wage work, plot size, use of animal traction, access to extension services, greenness of the location of the household/plot. Similarly, the use of organic fertilizer is enhanced by gender of the plot manager, credit access, animal traction, greenness (negatively), and distance to nearest market. Intercropping is practiced mostly on male managed plots and is facilitated by wage employment, size and tenure of the plot, distance to market (negative).

High rainfall variability tends to favor the use of organic fertilizers, while at the same time decreasing households' propensity to use any of the other technologies. Similarly, high variability in the number of days where the maximum temperature is above 34 degree Celsius tend to discourage farmers from using any of the technologies on their plots. These underscore the importance of favorable climatic conditions on the adoption of improved agricultural technologies.

The extent to which the underlying technologies are used is facilitated by long-term rainfall variability, animal traction, extension access, plot ownership, non-agriculture work, education, and distance to markets

Given the strong correlation between extension access and adoption of improved seeds and inorganic fertilizer, it is important that agricultural extension agents in rural Nigeria be well resourced technically and financially so they will be able to reach smallholder households in rural areas with the knowledge and benefits of these technologies.

Finally, the adoption of improved agricultural practices has potential to impact household welfare beyond plot-level productivity. Thus, future studies need to examine the welfare (food security, consumption, dietary diversity) implications of adopting multiple agricultural technologies in rural Nigeria.

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Table 1: Definition of variables and summary statistics

Variable	**Definition**	Mean	Std dev.
Improved Seeds	1 if improved seed was planted on plot during the 2018/19 agricultural season	0.05	0.22
Inorganic Fertilizer	1 if inorganic fertilizer was used on plot during the 2018/19 agricultural season	0.44	0.50
Organic fertilizer	1 if the organic fertilizer was used on plot during the 2018/19 agricultural season	0.35	0.48
Legume intercropping	1 if the plot was intercropped with a leguminous crop during the 2018/19 agricultural season	0.36	0.48
Productivity	Ln value of crop harvest per hectare	10.00	1.47
Household Size	Number of persons in the household	6.84	3.64
Dependency	Share of dependents in the household	1.20	1.13
Gender	1 if the plot manager is a male	0.89	0.32
Age	Age of the plot manager in years	48.93	13.96
Education	Number of years of formal education of the plot manager	5.69	4.56
Off farm	1 if the plot manger works off farm	0.49	0.50
Wage work	1 if the plot manger has a wage work	0.15	0.36
Credit	1 if the household had access to credit	0.12	0.33
Remittance	1 if the household received international remittance	0.02	0.14
Extension	1 if the household had access to extension services	0.21	0.40
Plot size	Ln plot size (ha)	-1.16	1.29
Owned land	1 if the plot was owned by the household during the 2018/19 season	0.77	0.42
Purestand	1 if the household had at least one purestand plot	0.30	0.46
Machinery	1 if tractor services were used on plot	0.10	0.29
Animal traction	1 if animal traction was used on plot	0.27	0.45
Erosion	1 if there is erosion control facility on plot	0.03	0.16
Soil quality	1 if the perceived quality of soil on plot is good	0.85	0.36
Steep slope	1 if plot has a steep slope	0.21	0.41
Irrigation	1 if the plot was irrigated during the 2018/2019 agricultural season	0.03	0.17
Fertilizer Price	Average price of a Kg of inorganic fertilizer (NPK or urea)	150.84	89.57
Distance	Distance from homestead to nearest market (Km)	62.19	48.77
Nutrient constraint	Nutrient availability constraint (1-4 scale, 5 = mainly water)	1.79	0.79
NDVI	Long-term average NDVI (greenness) value in primary growing season (highest quarter)	0.29	0.04
Distance to household	Distance from plot to homested (Km)	1.37	5.06
Wetness index	Potential Wetness Index	14.82	3.44
CV of rainfall	Coefficient of variation of rainfall during the growing season	0.68	0.17
CV of GDD	Coefficient of variation of growing degree days during growing season	0.23	0.20
CV days temp	Coefficient of variation of number of days where temperature is greater than 34C during the growing season	1.00	1.08
Region	1 if the household is located in North Central, North East or North West	0.71	0.45

Table 2: Joint and marginal probabilities of adoption of agricultural technologies (%)

Percent adopting in:	Joint probability	Marginal probabilities			
		Improved Seeds	Inorganic fertilizer	Manure	Legume Intercropping
Improved seed only	2.07	2.07			
Fertilizer only	15.52		15.52		
Manure only	4.45			4.45	
Intercropping only	6.80				6.80
Improved seed and fertilizer	0.96	0.96	0.96		
Improved seed and manure	0.43	0.43		0.43	
Improved seed and intercropping	0.13	0.13			0.13
Fertilizer and manure	7.13		7.13	7.13	
Fertilizer and intercropping	6.69		6.69		6.69
Manure and intercropping	9.50			9.50	9.50
Improved seed, fertilizer, manure	0.81	0.81	0.81	0.81	
Improved seed, fertilizer, intercropping	0.47	0.47	0.47		0.47
Improved seed, manure, intercropping	0.14	0.14		0.14	0.14
Fertilizer, manure, intercropping	11.81		11.81	11.81	11.81
All four	0.26	0.26	0.26	0.26	0.26
None (plot did not receive any technology)	32.81				
Total	**100.00**	**5.28**	**43.65**	**34.53**	**35.80**

Table 3: Conditional and unconditional adoption probabilities

Condition	Improved Seeds	Inorganic fertilizer	Manure	Legume Intercropping
$P(Y_j = 1)$	0.05	0.44	0.35	0.36
$P\left(Y_j = 1 \middle\| Y_s = 1\right)$	1	0.06	0.05	0.03
$P\left(Y_j = 1 \middle\| Y_F = 1\right)$	0.47	1	0.58	0.54
$P\left(Y_j = 1 \middle\| Y_M = 1\right)$	0.31	0.46	1	0.61
$P\left(Y_j = 1 \middle\| Y_L = 1\right)$	0.19	0.44	0.63	1
$P\left(Y_j = 1 \middle\| Y_s = 1, Y_F = 1\right)$	1	1	0.43	0.29
$P\left(Y_j = 1 \middle\| Y_s = 1, Y_M = 1\right)$	1	0.65	1	0.24
$P\left(Y_j = 1 \middle\| Y_s = 1, Y_L = 1\right)$	1	0.73	0.40	1
$P\left(Y_j = 1 \middle\| Y_F = 1, Y_M = 1\right)$	0.05	1	1	0.60
$P\left(Y_j = 1 \middle\| Y_F = 1, Y_L = 1\right)$	0.04	1	0.63	1
$P\left(Y_j = 1 \middle\| Y_M = 1, Y_L = 1\right)$	0.02	0.56	1	1
$P\left(Y_j = 1 \middle\| Y_S = 1, Y_F = 1, Y_M = 1\right)$	1	1	1	0.24
$P\left(Y_j = 1 \middle\| Y_S = 1, Y_F = 1, Y_L = 1\right)$	1	1	0.35	1
$P\left(Y_j = 1 \middle\| Y_S = 1, Y_M = 1, Y_L = 1\right)$	1	0.64	1	1
$P\left(Y_j = 1 \middle\| Y_F = 1, Y_M = 1, Y_L = 1\right)$	0.02	1.00	1	1

Table 4: Determinants of adoption - multivariate probit model

	Improved Seeds		Inorganic Fertilizer		Organic Fertilizer		Legume Intercropping	
Variable	Coefficient	Std dev.	Coefficient	Std dev.	Coefficient	Std dev.	Coefficient	Std dev.
Household Size	0.016	0.011	0.009	0.007	0.006	0.007	-0.005	0.009
Dependency	0.021	0.032	-0.021	0.019	0.005	0.027	-0.011	0.022
Gender	-0.179	0.132	-0.319***	0.083	0.185*	0.097	0.215**	0.105
Age	-0.018	0.017	-0.041***	0.010	0.008	0.011	0.018	0.013
Age squared	0.000	0.000	0.000***	0.000	0.000	0.000	0.000	0.000
Education	0.024***	0.008	0.023***	0.005	-0.009*	0.006	0.005	0.006
Off farm	0.196***	0.075	0.174***	0.045	0.176***	0.049	0.063	0.062
Wage work	0.024	0.113	0.221***	0.064	-0.218***	0.079	0.171**	0.084
Credit	-0.041	0.111	-0.240***	0.063	0.217***	0.076	0.103	0.092
Remittance	0.683***	0.201	-0.285*	0.152	-0.508**	0.203	-0.040	0.195
Extension	0.293***	0.089	0.390***	0.052	-0.053	0.062	0.003	0.069
Plot size	-0.051	0.060	0.066*	0.036	0.038	0.047	0.323***	0.046
Owned land	0.008	0.167	0.104	0.115	0.189	0.132	0.284**	0.128
Machinery	-0.556	0.629	0.155	0.222	0.143	0.249	0.002	0.245
Animal traction	0.109	0.179	0.066	0.131	0.557***	0.151	0.339**	0.148
Erosion	0.565	0.560	0.380	0.429	-0.155	0.418	0.309	0.561
Soil quality	-0.044	0.186	0.017	0.104	0.106	0.125	0.252**	0.131
Steep slope	0.152	0.139	-0.115	0.093	0.071	0.107	0.006	0.116
Irrigation	-0.298	0.401	0.385	0.281	-0.373	0.259	-1.529***	0.325
Fertilizer Price	0.000	0.000	0.001*	0.000	0.000	0.000	0.000	0.000
Distance market	-0.001	0.001	-0.006***	0.000	-0.003***	0.001	-0.002***	0.001
Nutrient const.	0.121*	0.066	-0.012	0.037	0.039	0.042	0.006	0.065
NDVI	0.016	1.435	-11.530***	0.976	-1.574	1.139	-1.575	1.972
Distance house	-0.015	0.034	-0.010	0.015	-0.020	0.021	-0.028	0.017
Wetness index	0.012	0.021	0.007	0.010	-0.002	0.010	0.004	0.009
CV of rainfall	-0.710	0.546	-1.420***	0.326	3.888***	0.351	0.714	0.756
CV of GDD	-0.386	0.344	-1.703***	0.199	-0.583***	0.185	1.419***	0.215
CV days temp	-0.064	0.082	-0.894***	0.094	-0.350***	0.097	0.006	0.202
Region	0.344	0.228	0.070	0.137	-0.288*	0.152	1.674***	0.204
Constant	-0.585	0.865	7.064	0.564	-3.235	0.674	-2.127	1.170
Joint significance of Mean of Plot-varying Covariates [χ2 (44)]			967.11	(*p*=0.00)				
Sample size			6376					
Wald			4639.99	(*p*=0.00)				

*, ** and *** indicate statistical significance at 10, 5 and 1%, respectively.

Table 5. Estimated covariance matrix of the multivariate probit model regression between agricultural technologies

	ρ_S	ρ_F	ρ_M	ρ_L
ρ_S	1			
ρ_F	0.124***	1		
ρ_M	0.040	-0.134***	1	
ρ_L	-0.039	-0.097***	0.117***	1
Likelihood ratio test of: $\rho_{SF} = \rho_{SM} = \rho_{SL} = \rho_{FM} = \rho_{FL} = \rho_{ML} = 0$ $(\chi^2(6) = 1200, P = 0.000)$				

*, ** and *** indicate statistical significance at 10, 5 and 1%, respectively.

Table 6: Intensity of adoption – ordered probit model results

Variable	Pooled Ordered Probit							Random Effects Ordered Probit	
			Marginal Effects						
	Coeff	Std error	Prob (Y = 0 | X)	Prob (Y = 1 | X)	Prob (Y = 2 | X)	Prob (Y = 3|X)	Prob (Y = 4 | X)	Coeff	Std error
Hous Size	0.004	0.00	-0.001	-0.001	0.001	0.000	0.0000	0.016	0.01
Dependency	-0.002	0.01	0.001	0.000	-0.001	0.000	0.0000	0.003	0.04
Gender	-0.044	0.05	0.010	0.007	-0.011	-0.006	0.0000	-0.144	0.15
Age	-0.011*	0.01	0.003*	0.002*	-0.003*	-0.001*	0.0000	-0.016	0.02
Age squared	0.000**	0.00	0.000**	0.000**	0.000**	0.000**	0.0000*	0.000	0.00
Education	0.008**	0.00	-0.002*	-0.001**	0.002***	0.001**	0.0000*	0.017*	0.01
Off farm	0.190**	0.03	-0.044***	-0.030***	0.049***	0.025***	0.0002***	0.341***	0.08
Wage work	0.084*	0.05	-0.019*	-0.014*	0.021**	0.011*	0.0001	0.149	0.12
Credit	-0.067*	0.04	0.016*	0.010*	-0.018*	-0.008*	-0.0001	-0.063	0.12
Remittance	-0.199*	0.12	0.051	0.025**	-0.053*	-0.023**	-0.0001**	-0.321	0.32
Extension	0.183***	0.03	-0.041***	-0.032***	0.046***	0.026***	0.0002***	0.277***	0.09
Plot size	0.185***	0.02	-0.043***	-0.029***	0.048***	0.024***	0.0002***	0.337***	0.04
Owned land	0.158**	0.08	-0.039*	-0.023**	0.042**	0.019**	0.0001*	0.298***	0.12
Machinery	0.072	0.15	-0.016	-0.012	0.018	0.010	0.0001	0.062	0.27
Animal traction	0.367*	0.08	-0.082***	-0.063***	0.092***	0.052***	0.0004**	0.543***	0.14
Erosion	0.100	0.20	-0.022	-0.017	0.025	0.014	0.0001	0.064	0.31
Soil quality	0.088	0.07	-0.021	-0.013	0.023	0.011	0.0001	0.108	0.12
Steep slope	-0.096	0.06	0.023	0.014*	-0.025	-0.012*	-0.0001	-0.175*	0.10
Irrigation	-0.593***	0.15	0.177***	0.033***	-0.159***	-0.051***	-0.0002**	-0.944***	0.31
Fert. Price	0.000	0.00	0.000	0.000	0.000	0.000	0.0000	0.000	0.00
Distance to market	-0.004***	0.00	0.001***	0.001***	-0.001***	0.000***	0.0000***	-0.005***	0.00
Nutrient constraint	-0.041	0.03	0.010	0.007	-0.011*	-0.005	0.0000	-0.082	0.07
NDVI	-7.117***	0.63	1.667***	1.128***	-1.855***	-0.933***	-0.0062***	-12.137***	1.61
Distance to house	-0.016*	0.01	0.004*	0.002*	-0.004*	-0.002*	0.0000*	-0.023	0.02
Wetness index	0.002	0.01	-0.001	0.000	0.001	0.000	0.0000	0.004	0.01
CV of rainfall	1.974***	0.22	-0.462***	-0.313***	0.514***	0.259***	0.0017***	3.480***	0.56
CV of GDD	-0.679***	0.11	0.159***	0.108***	-0.177***	-0.089***	-0.0006***	-1.219***	0.32
CV days temp	-0.403***	0.08	0.094***	0.064***	-0.105***	-0.053***	-0.0003***	-0.517***	0.15
Region	0.355***	0.10	-0.094***	-0.040***	0.096***	0.039***	0.0002***	0.703***	0.23
Log likelihood			-6942.155					-5882.753	
Wald [χ2 (40)]			2878.95	(p=0.00)				843.07	(p=0.00)
Joint significance of Mean of Plot-varying Covariates [χ2 (11)]			468.55	(p=0.00)				193.31	(p=0.00)
μ_1	-2.17	0.38						-3.32	0.95
μ_2	-0.96	0.38						-1.38	0.94

μ_3	0.34	0.38	0.71	0.94
μ_4	2.36	0.39	3.92	0.96

*, ** and *** indicate statistical significance at 10, 5 and 1%, respectively.

Table 7: Impact of technologies on productivity

	Log (value of harvest Naira/ha)			
	OLS		**IVREG2H**	
Variable	Coefficient	Std Error	Coefficient	Std Error
Improved Seeds	0.217***	0.055	0.145*	0.084
Inorganic Fertilizer	0.304**	0.029	0.657***	0.087
Organic fertilizer	-0.002	0.033	-0.178***	0.066
Legume intercropping	-0.271***	0.041	-0.443***	0.059
Household Size	-0.002	0.004	-0.002	0.004
Dependency ratio	0.033**	0.013	0.034***	0.013
Gender	0.230***	0.048	0.237***	0.049
Age	-0.001	0.001	-0.001	0.001
Education	-0.007**	0.003	-0.011***	0.003
Off farm	-0.008	0.028	-0.011	0.030
Wage work	-0.061	0.045	-0.088*	0.046
Extension	0.061*	0.035	0.028	0.037
Own plot	0.133***	0.034	0.132***	0.035
Purestand	0.849***	0.039	0.762***	0.044
Erosion control	-0.036	0.111	-0.066	0.110
Soil quality	-0.049	0.037	-0.025	0.038
Steep slope	-0.112***	0.034	-0.094***	0.035
Irrigation	0.351***	0.093	0.279***	0.093
Distance to market	-0.001***	0.000	-0.001**	0.000
Nutrient constraint	-0.114***	0.022	-0.093***	0.023
Longterm NDVI	-4.372***	0.673	-5.431***	0.704
NDVI in 2018	4.217***	0.484	5.076***	0.539
Total rainfall in 2018	0.001***	0.000	0.000***	0.000
Start of wettest dekad in 2018	-0.027***	0.007	-0.018**	0.007
Distance to household	-0.003	0.003	-0.004	0.003
Wetness index	-0.009**	0.004	-0.007*	0.004
Region	-0.015	0.080	-0.057	0.085
Constant	11.096***	0.260	11.125***	0.281
Sample size	7,468		7,450	
R^2	0.222		0.203	
Hansen J statisitc			2.089	
Under identification test			763.385***	
Weak identification test			11.327**	

*, ** and *** indicate statistical significance at 10, 5 and 1%, respectively.