A Latent Class Analysis of Agricultural Technology Use Behavior in Uganda and Implications for Optimal Targeting

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Abstract:

Agricultural productivity is still very low in Africa largely due to low use of improved agricultural technologies. Existing adoption studies are marred by univariate analyses, often focusing on single technologies over a limited scope while assuming uniform effects of the explanatory variables across farm households. In this study, we use a large dataset that covers a wide geographical and agricultural scope to describe use-patterns of improved agro-technology in Uganda. Using latent class analysis, and over 12,500 households collected across the four regions of Uganda, we classify farmers based on the package of improved agro-technologies used. We find that the majority of farmers (61%) do not use any improved agricultural practices ('non-users') while only 5% of the farmers belong to the class of 'intensified diversifiers', using most of the commonly available agro-technologies across crop and livestock enterprises. Using multinomial regression analysis, we show that education of the household head, access to extension messages and affiliation to social groups, are the key factors that drive switching from the 'non-user' reference class to the other three preferred classes that use improved agro-technologies to varying levels. Results reveal that different farmer categories with different agro-technology needs, which may have implications for optimal targeting.

Acknowledegment: The authors would like to thank the International Institute for Impact Evaluation (3ie) for financial support. This work was undertaken as part of the CGIAR Research Program on Policies, Institutions, and Markets (PIM) led by the International Food Policy Research Institute (IFPRI).

JEL Codes: O33, D13

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Abstract

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***Key words*:** technology adoption, latent class analysis, multinomial regression, Uganda

1. Introduction

Africa has registered some progress regarding agricultural production in the recent past. This however is generally attributed to the opening of more land and mobilization of a larger agricultural labor force than improvement in productivity (Blein *et al*., 2013). Evidence has linked this to a number of reasons, such as co-existence of substantial adoption heterogeneities across farm households, and a lack of a suitable mix of technologies for farmers to take advantage of, thereby limiting the productivity potential (Abay *et al*., 2016). For the case of Uganda, strikingly low adoption rates for potentially beneficial agricultural technologies is linked to factors related to constrained social learning, credit constraints, supply constraints, transaction costs, and other market imperfections (Duflo *et al*., 2009; Munasib *et al*., 2015). The situation is not helped by the nature of various government interventions over the past two decades, implying that adoption of the necessary innovations cannot be simply decreed but rather must meet the needs of producers (Blein *et al*., 2013).

Technology adoption in agriculture is probably one of the most studied topics in agricultural and behavioral economics. However, most studies focus on a single technology and typically make the *a priori* assumption that the effects of explanatory factors do not vary across farm households (Abay *et al*., 2016). It is understandable that this is usually limited by sample sizes, but generalizations on the assumption of the "average" farmer across a wider scope may be misleading. For informed policy making, it is important to identify which category of farmers ought to be targeted by what kind of support under the existing policy framework.

In this study, we use a large dataset that typically covers a wider geographical and agricultural scope to describe improved technology use in Uganda. Then, we employ statistical methods to group farmers into distinct classes based on the package of improved agro-technologies mix. We estimate user rates and the key technology components that define this classification. Using multinomial regression analysis, we identify and estimate factors that would facilitate households' switching from the undesired situation (of non-user) to the other three preferred farmer classes with respect to agricultural production. We find that improved seeds, pesticides[1] and fertilizer are the most commonly used crop technologies while veterinary drugs are the most commonly used technology for livestock farmers. We are able to identify four farmer classes in our data, with the majority (61%) being non-users, while 'intensified diversifiers' comprise of only 5%. Education, access to agricultural extension and affiliation to social groups, of course with varying intensities, are the key factors that drive switching from the non-user category to the other three classes. This study has identified Uganda's different farming groups based on adopted agricultural technologies and their socio-economic characteristics; and that any positive shift in some of these socio-economic characteristics facilitates movement away from a less advanced group to more advanced group. This is a great contribution of our study to the existing adoption literature.

The rest of the paper is organized as follows: Section 2 presents data and methods while Section 3 presents the results and discussion. Section 4 presents the concluding summary of the findings.

2. Data and Methods

2.1. Sampling and data collection

This paper uses baseline survey data which was collected as part of an ongoing impact evaluation of community advocacy forums (Citizen Barazas) on public service delivery in Uganda, focusing on key sectors: agriculture, health, education, drinking water and

[1] In this paper, we have combined pesticides and herbicides which are both defined by pesticides.

infrastructure. Citizen Barazas are viewed as platforms for enhancing information sharing between policy makers, development partners and beneficiaries of public goods and services. Barazas also provide citizens the opportunity to ask questions to their leaders and deliberate among themselves, with the intention of contributing to effective monitoring, accountability and transparency among all stakeholders. The baseline survey is substantial in size, comprising of 12,560 randomly selected households from 40 districts across four regional blocks of Uganda (i.e. Northern, Western, Central and Eastern) to capture the diverse characteristics in terms of ethnicity, geographical, agro-ecological conditions, and cultural history of each region. The selection of the final sample followed a series of steps that would ensure random representation of study areas and households as a cardinal requirement for a good social experiment (for more details on the sampling design, see Kabunga *et al*., 2015). However, 40 households were dropped during data cleaning due to missing data on most of the variables. Consequently, a final sample of 12,520 households were retained for analysis in this study. Noteworthy and as would be expected for Uganda, most households were rural-based and dependent on agriculture.

Data collection took place between June and August 2015. Household interviews were conducted face-to-face by trained enumerators using Computer Assisted Personal Interviewing (Samsung Galaxy Tab 2 devices). The survey questionnaire was designed using Open Data Kit (ODK) and took about one hour to administer. The survey questionnaire captured data on household demographics, locational characteristics, assets, and details on assessing the quality and quantity aspects of public service delivery in the aforementioned sectors. Under the agricultural sector, interviews sought to understand the pattern of use of agricultural technologies among surveyed households.

2.2. Data Analysis

We employ both descriptive analysis and econometric methods through latent class analysis models to explore response patterns inherent within the data as far as agricultural technology use is concerned. Based on generated classes, we specify multinomial regression models that predict individual, household and contextual characteristics that determine class membership. Descriptive methods include sample statistics and correlations to describe agricultural technology use patterns in Uganda. Where appropriate, graphs are used to show visual relationships within the data.

Latent class analysis (LCA) is a statistical method that allows an analyst to generate an array of discrete, mutually exclusive latent classes of individuals that represent the response patterns in the data, the prevalence of each latent class and the amount of error associated with each variable in measuring these latent classes (Collins & Lanza, 2010). LCA is used to reveal underlying classes based on multiple variables that are characterized by a pattern of conditional probabilities.

In this study, households were asked to mention the various types of agricultural technologies (for both crop and livestock enterprises) they used in the previous year. These, coded as binary (use/non-use) were used in a probabilistic framework as explanatory variables to define the latent classes of technology combinations that characterize Uganda farming households.

Assume that our sample is composed of a number of different groups, and an individual's preference group is latent or unobserved. What we observe is the individual's choice of agricultural technologies and possibly other characteristics. The latent class model that we employed is described as follows (Lanza *et al*., 2009; Lanza *et al*., 2015). We estimate a latent class model with M classes from a set of Q categorical items and include a continuous or binary covariate X. Let the vector $Y_i = (Y_{i1},......,Y_{iQ})$ represent individual i's responses to the Q items, where the possible values of Y_{iq} are $1,......,r_q$. Let $L_i = 1, 2, \dots, m_c$; be the latent class membership of individual i, and let $I(y = k)$ be the indicator function that equals 1 if $y = k$, and 0 otherwise. Let the last class be the reference class. Let X_i represent the value of the covariate for individual i. The covariate may be related to the probability of membership in each latent class, γ, but is assumed to be otherwise unrelated to Y_i. Then the contribution by individual i to the likelihood is:

$$P(Y_i = y \mid X_i = x) = \sum_{i=1}^{M} \gamma_l(x) \prod_{q=1}^{Q} \prod_{k=1}^{r_q} \rho_{qk|l}^{I(y_q = k)} \tag{1}$$

where the ρ parameters are the item-response probabilities conditional on class membership while the β parameters in Equation (2) below are the coefficients in logistic regressions using the covariate X to model the latent class membership parameters, γ. The γ parameters can be expressed as

$$\gamma_l(x) = P(L_i = l \mid X_i = x) = \frac{\exp(\beta_{0l} + x\beta_{1l})}{\sum_{j=1}^{M} \exp(\beta_{0j} + x\beta_{1j})} = \frac{\exp(\beta_{0l} + x\beta_{1l})}{1 + \sum_{j=1}^{M-1} \exp(\beta_{0j} + x\beta_{1j})} \tag{2}$$

for $l = 1,2,.....,M$. The latter two terms on the right are equal because we assume that the last (i.e., the M^{th}) class is used as the reference class. The reference class has its βs constrained to zero, since the relative probabilities of being in the other classes are being compared to the probability of this reference class. It is necessary to set the βs for some class to zero for the sake of model identifiability, because of the natural constraint that the probabilities for all classes must sum to one for each individual, but it need not be the last class. The choice of reference class does not affect the final fitted probability estimates for any individual or class.

The ρ parameters express the correspondence between the observed items and the latent classes, and form the basis for interpretation of the latent classes. Since our model includes covariates, only ρ and β parameters are estimated; while the γ parameters are calculated as functions of β parameters and the covariates.

This model allows us to estimate the log odds that individual i falls in latent class l relative to the reference class. For example, if class 1 is the reference class, then the log odds of membership in class 4 relative to class 1 for an individual with value x on the covariate is

$$\log\left(\frac{\gamma_4(x)}{\gamma_1(x)}\right) = \beta_{04} + \beta_{44}x \tag{3}$$

Exponentiated β parameters are odds ratios, reflecting the increase in odds of class membership (relative to reference class M) corresponding to a one-unit increase in the covariate.

Since the model involves more than three latent classes, we implement a baseline-category multinomial logistic regression to predict latent class membership. We specify a comparison class with all other latent classes combined into one reference group. Common covariates are then used to predict membership in the specific class relative to the rest. This option predicts a more conservative model and may be more useful in cases where the multinomial logistic regression model is not estimable due to smaller samples (Lanza *et al*., 2015).

Literature suggests several approaches for assessing the fit of LCA models. In this study, the number of latent classes that best fit of our model are determined based on the Bayesian Information Criterion (BIC) statistic. The BIC is based on the likelihood function that measures the quality of the model while introducing penalty terms in order to reduce model overfitting, and is preferred when sample sizes are large enough (Dziak *et al*. 2014). To show robustness, we also perform other tests of model fit including the Likelihood Ratio and the Akaike's Information Criterion (AIC).

3. Results and Discussion

3.1. Descriptive analysis

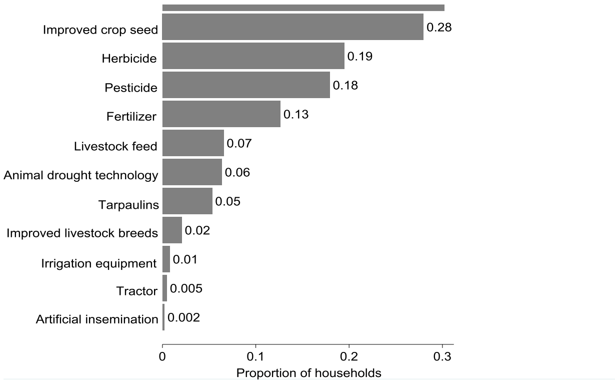
In the survey, we inquired to what extent farmers used commercial inputs innovated with crops or livestock in the one-year period preceding the survey. Surprisingly, 63% of surveyed farmers reported to have used at least one agriculture technology in the preceding year (Table 1). While there is a gender discrepancy in this use of agro-technologies, at least half of female-headed households (51%) reported using these technologies as well. Table 1 also shows a positive correlation between farm size and use of agro-technologies: 70% of farmers with land larger than 4 acres used improved agricultural inputs.

Table 1: Use of agricultural inputs

All	62.5%
Gender of household head	
Male	65.2%
Female	50.8%
Farm size	
< 2 acres	53.9%
2 - 4 acres	63.9%
> 4 acres	69.7%

These averages, however, hide a large degree of heterogeneity among the use of the various agricultural technologies. Figure 1 shows this heterogeneity: The most widely used agro-technologies are veterinary drugs for livestock, followed by the application of improved seed (30% and 28% of households, respectively). The other agro-technologies most frequently used are herbicide (19%), pesticide (18%), and fertilizer (13%). Other improved inputs and elements in mechanized production, such as animal improved livestock feed, animal draught equipment, and tarpaulins are used at a much lower rate of about 5-7%. Yet others are hardly used at all, including irrigation, tractor, artificial insemination, and improved livestock breeds.

Figure 1: Use of advanced inputs



We examine whether there are differences by land endowment in the use of key agricultural technologies for crop production, namely improved seed, fertilizer, and pesticide (Figure 2). While the share of households who use pesticide and improved seed is larger for farmers with larger acreage, it is striking to find that fertilizer use does not vary much across the different land size categories. In fact, this share is slightly smaller for the large-land operators of above 4 acres. This could be for various reasons, among others, a possible substitution from crops that most benefit from the use of inorganic fertilizer, to crops that need less or no fertilizer at all.

Still, considering the two most commonly used inputs across all farms, we find consistent patterns that the rate of veterinary drug use starts outpacing that of improved seed as farm size increases (Figure 3). For example, low-endowed households use improved seed (25%) at a higher rate than livestock drugs (20%). For the households with medium level of land endowment, the use rate is about the same. However, 41% of large farmers make use of livestock drugs, while only 31% of them use improved seed. This may reflect a different commodity portfolio in that large land holders may be more likely to rear livestock.

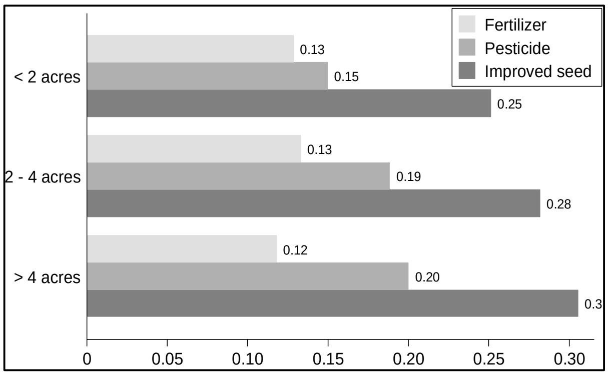


Figure 2: Use pattern of three key agricultural technologies by farm size

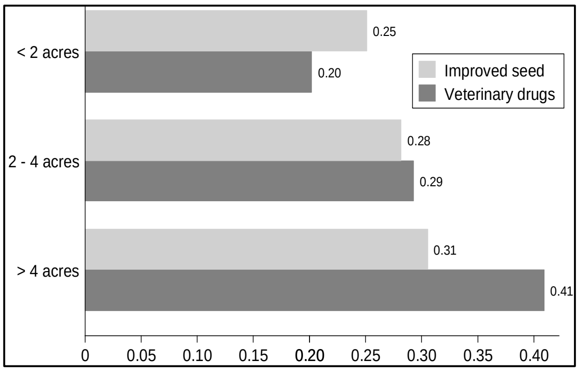


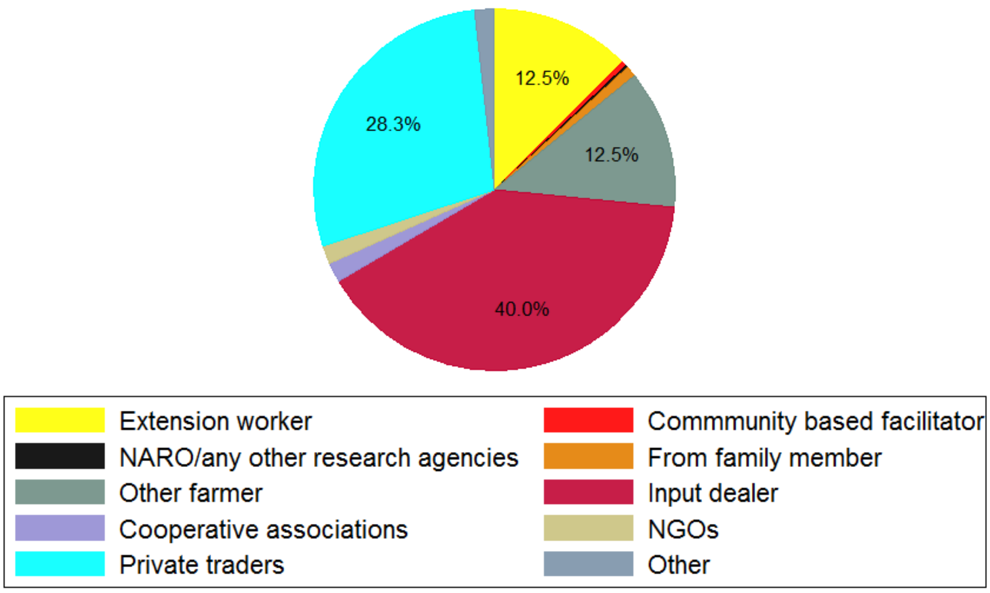
Figure 3: Use pattern of two most commonly used agricultural technologies by farm size

We also obtained information on the source from which farmers obtain their inputs. Figure ***4*** shows the relative importance of different sources for improved seed. The most important providers are input dealers[2], from whom 40% of households access their improved seed. The next largest group are private traders[3]: 28% of households use them as a source for improved seed. Likely, farmers have multiple relationships with them in that they sell to them

[2] Input dealers buy and sell (deal in) agricultural farm inputs such as improved crop seeds, veterinary drugs, fertilizers, pesticides, herbicides etc. to farmers as their main business.
[3] Private traders are the agricultural produce dealers who buy and pass on modern agricultural inputs to farmers either on cash or in exchange of produce upon harvest.

their output, part of which may have gone toward repaying them for improved seeds they received before the planting period. Following private traders, other farmers are also an important source for getting improved seed, for 13% of the respondents. While local seed exchange among farmers are common in developing countries, it is interesting to note that farmers apparently also sell improved varieties. A similarly important provider are extension agents (13%). All other providers are fairly unimportant in the extent to which they are used by farmers to obtain improved seed. This includes NGOs, community-based facilitators, agricultural research organizations, and agricultural cooperatives.

Figure 4: Sources from whom farmers purchased/obtained improved seed



For resource-poor farmers, adopting agricultural technologies is an intensive process driven by expected benefits, but also requiring one to choose the right mix of one or more technologies under uncertain circumstances (Bold *et al*., 2015; Abay *et al*., 2016). Yet, the decision to adopt a technology (or its component) may depend on the presence of another complementary technology (or component) (Khanna, 1999). A separate bivariate analysis shows low rates of joint technology adoption in Uganda, a situation that cannot cause desired positive change in yields and farm incomes. In the next sections, we use econometric methods to explore a large dataset and draw patterns of agricultural technology combination, and then determine the factors driving such technology combinations.

3.2. Latent Class Analysis (LCA) model results

(a) Classification

The estimation of the LCA revealed that the BIC value is lowest at the fourth class (and is efficient and robust to other fit tests—AIC and Likelihood Ratio — (see Appendix I). This implies that four latent groups can be identified in the dataset based on individual agricultural technology use heterogeneity. The majority of households (61%) fall in Class I while the minority is observed in Class IV (5%) with only 394 households (Table 2). As expected, individual class size should sum up to total sample size as every individual theoretically can only belong to one class. For each latent class, we estimate the item-response probability of using a given set of agricultural technologies. As a rule, probabilities ≥ 0.50 are considered sufficient enough to influence classification as half of class members were more likely to respond affirmatively "yes" to the use of a given technology. Consequently, these probabilities provide the basis for labeling the respective classes.

Table 2: Latent class prevalence and item-response probabilities for four class model of agricultural technology adoption

	Latent Class			
	I	II	III	IV
	'Non-users'	'Specialized livestock farmers'	'Specialized crop farmers'	'Intensive Diversifiers'
Latent class prevalence (%)	61.3	19.7	14.2	4.8
Probability of a 'yes' response:				
Fertilizers	0.00	0.00	**0.69**	**0.60**
Pesticides	0.12	0.39	**0.65**	**0.92**
Improved crop seed	0.20	0.27	**0.53**	**0.59**
Livestock feeds	0.00	0.17	0.00	**0.64**
Veterinary drugs	0.07	**0.89**	0.30	**0.94**
Improved livestock breed	0.00	0.03	0.03	0.18
N	*7,814*	*3,006*	*1,306*	*394*

* Item-response probabilities ≥ 0.5 **bolded** to facilitate interpretation.

Accordingly, Class IV represents the highest item-response rates in most agricultural technologies except for the use of improved livestock breed[4] (Table 2). This implies that households in this class reported being most likely to use almost all the listed agricultural technologies. Because of this, we prefer to label this class 'intensive diversifiers'. Class III represents farmers whose item-response probability is only high for crop-based technologies (fertilizer, pesticide and improved seed). Because of this, we label this class 'specialized crop farmers'. Class II has only one technology—veterinary drugs—with high response probability, while Class I shows the least probability of members using any of the listed agricultural technologies. We thus label Class II and Class I as 'specialized livestock farmers' and 'non-users', respectively. Labeling Class II as such is justified even if there is only one key input because, unlike cropping systems, the single most important technology for livestock farmers in Uganda are veterinary drugs.

[4] The use of improved livestock breed is combined with the use of artificial insemination which is labelled improved livestock breed.

(b) Class characteristics

After identifying the key groups in our data, it is interesting to examine the salient contrasts across class membership. Using 'non-users' as reference, we compare individual farmer, household, institutional, contextual and locational characteristics of each class by simply performing tests of equality. Results of these comparisons are presented in Table 3.

Table 3: Distribution of Class membership by demographic characteristics

	Non-users (N=7,814)		Specialized livestock farmers (N=3,006)		Specialized crop farmers (N=1,346)		Intensive diversifiers (N=394)	
	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.
Farmer characteristics								
Age	46.42	0.171	1.71***	0.317	-3.40***	0.438	0.73	0.772
Education	5.74	0.042	0.73***	0.082	1.55***	0.111	2.94***	0.196
Gender	0.22	0.005	-0.06***	0.009	-0.12***	0.012	-0.11***	0.021
Household size	6.03	0.031	0.93***	0.060	0.36***	0.081	1.21***	0.143
Farm assets/resources								
Land parcels	1.88	0.014	0.11***	0.027	0.42***	0.039	0.51***	0.065
Total landholding	5.33	0.402	7.05***	0.881	0.32	0.997	8.60***	1.983
Land user rights	0.87	0.004	0.03***	0.007	0.05***	0.010	0.09***	0.017
Radio ownership	0.44	0.006	0.12***	0.011	0.14***	0.015	0.25***	0.026
Mobile phone ownership	0.64	0.005	0.19***	0.010	0.19***	0.014	0.27***	0.024
Institutional factors								
Distance to market	2.49	0.100	0.05	0.217	0.12	0.271	1.67***	0.493
Distance to all-weather road	2.47	0.075	-0.49***	0.129	0.64***	0.192	-0.21	0.344
Distance to the sub county	6.71	0.066	1.14***	0.187	-0.86***	0.170	-0.59**	0.303
Storage facility	0.11	0.004	-0.01	0.007	-0.04***	0.009	-0.05***	0.016
Distance to water source (dry season)	6.95	0.105	-0.48***	0.192	0.29	0.273	-0.27	0.479
Distance to water source (wet season)	0.64	0.009	-0.06***	0.018	-0.08***	0.025	-0.24***	0.043
Extension visit	0.06	0.003	0.05***	0.006	0.09***	0.008	0.14***	0.013
Farmer association	0.34	0.005	0.03***	0.010	0.05***	0.014	0.11***	0.025
Physical location								
Residence	0.09	0.003	0.002	0.006	-0.03***	0.008	0.02	0.015
Altitude (m.a.s.l)	1193.4	3.2	16.1***	5.9	158.1***	9.7	137.7***	14.4
Central	0.21	0.005	0.07***	0.009	0.20***	0.012	0.35***	0.021
Eastern	0.23	0.005	-0.13***	0.008	0.15***	0.013	-0.05**	0.022
Northern	0.31	0.005	-0.11***	0.010	-0.24***	0.013	-0.30***	0.023
Western	0.25	0.004	0.17***	0.010	-0.11***	0.012	0.002	0.022

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

Table 3 shows that the average age of household heads in the reference class (Non-users) is 46.4 years. Non-users are significantly older (by 3.4 years) than specialized crop farmers but significantly younger when compared to specialized livestock farmers. There is no significant age difference between non-users and diversifiers. Education of the household head, as also reported elsewhere (Feder *et al*., 1985; Kabunga, *et al*., 2012), is key in agricultural technology adoption. All the three classes have significantly higher education than the reference group. Diversifiers have, on average, 3 years of additional education when compared to non-users. Majority households are male-headed (78%). It seems use of agricultural technologies gets significantly more constrained for female-headed households. An average household is composed of 6 people in the reference group yet there are indications that higher family size may significantly drive use agricultural technology among the specialized farming groups and the diversifiers.

Farm size and land user-rights are key determinants of technology adoption and use (Feder *et al*., 1985). Table 3 shows that diversifiers and specialized livestock farmers operate more than twice the farm size of the reference group. We do not observe significant differences in farm size between non-users and specialized crop farmers, implying that specialized crop farmers have no choice but to intensify on their small farms using improved seed, fertilizer and pesticides. Moreover, the share of non-users that reports insecure land ownership and user rights is significantly higher when compared to the other classes. Non-users are also constrained in terms of information access as the share of households that own radios and mobile phones is significantly lower in the non-user class compared to the rest.

Table 3 further shows that farming is a rural activity with generally poor access to the necessary infrastructure. On average, households travel over 2km to reach the nearest all-weather road or market. Households are located more than 6km from the sub-county headquarters. Surprisingly, intensive diversifiers are located far away from the markets than the other classes, which may imply that they face more constraints in accessing markets for their products compared to the rest of the groups. Water access problems are reported by all farmer classes especially in the dry season: On average, households travel for about 7km to reach the nearest water sources; this reduced by tenfold during the wet season. Water access problems may be primarily responsible for the low levels of irrigation technology use as earlier observed.

To gauge the extent to which households are engaged in social groups and extension services, we asked whether households had made visits to demonstration sites and/or extension offices in the year preceding the survey. We also asked farmers whether they are involved or affiliated to farmer groups that could act as alternative sources of agricultural information on technologies or inputs. Table 3 shows that only 6% of farmers in the non-users class reported having visited extension services or demonstration sites in the previous year. Not surprisingly, comparisons show significantly higher frequency visits to extension services and/or demonstration sites for the rest of the classes, with intensive diversifiers coming on top. With respect to group affiliation, we observe similar trends with significantly more members in the diversifiers class affiliated to social groups than the rest.

Farming is of course primarily rural based: only 9% of farmers reside in urban areas. The share of urban dwellers even reduces significantly to less than 7% for specialized crop farmers. Specialized crop farmers live on average at the highest altitude followed by intensifiers and then specialized livestock farmers. Non-users are living at the lowest altitude of about 1,200 m.a.s.l. The distribution of class membership by region indicates that the plurality of non-users (31%) are found in the northern region; 25% in the western region; 23% in the eastern region; and 21% in the central region. The plurality of diversifiers and specialized crop farmers are in central region (increase of 35% and 20%, respectively from the reference group) while the least share of these is recorded for the northern region.

(c) Predictors of Class Membership

Following the descriptive analysis of class membership above, we extend the analysis by conducting a joint (simultaneous) decision model (Khanna, 1999). We estimate the effects of covariates (predictors) on class membership in each class relative to the reference class (Class 1: "Non-users"). We then test these effects using multinomial logistic regression methods. Results are presented in Table 4. Estimates are marginal effects, which measure the percentage change in the probability of class membership when the value of the explanatory variable of interest changes by one unit (for continuous variables) or switches from 0 to 1 for indicator variables, when all other variables are kept constant at their means.

Table 4: Four-class LCA regression results for the effects of covariates on class membership (Non-users are the reference group)

	Specialized Livestock Farmers		Specialized Crop Farmers		Intensive diversifiers	
	Coef.	S.E	Coef.	S.E	Coef.	S.E
Constant	-3.624^{***}	0.305	-3.825^{***}	0.405	-8.864^{***}	0.811
Age	0.044^{***}	0.010	-0.008	0.015	0.085^{***}	0.029
Age squared	-0.000^{***}	0.000	-0.000	0.000	-0.001^{***}	0.000
Education	0.025^{***}	0.007	0.047^{***}	0.009	0.130^{***}	0.014
Gender	-0.215^{**}	0.103	-0.535^{***}	0.137	-0.451^{**}	0.214
Household size	0.073^{***}	0.009	0.017	0.013	0.093^{***}	0.020
Land parcels	0.064^{***}	0.019	0.171^{***}	0.023	0.181^{***}	0.035
Farm size	0.015^{***}	0.002	0.013^{***}	0.003	0.015^{***}	0.003
Farm size squared	-0.000^{***}	0.000	-0.000^{***}	0.000	-0.000^{***}	0.000
Land user rights	-0.099	0.079	0.101	0.119	0.195	0.264
Radio ownership	0.392^{***}	0.061	0.491^{***}	0.090	1.063^{***}	0.237
Phone ownership	0.452^{***}	0.061	0.470^{***}	0.088	0.375^{**}	0.195
Distance to nearest market	0.000	0.004	0.005	0.006	0.019^{***}	0.008
Squared distance to market	0.000	0.000	-0.000	0.000	-0.000	0.000
Distance to the sub county	-0.002	0.007	-0.032^{***}	0.009	-0.030^{**}	0.012
Squared distance to sub county	0.000^{*}	0.000	0.000^{*}	0.000	0.000^{**}	0.000
Storage facility	0.062	0.083	0.129	0.132	-0.003	0.254
Distance to all-weather road	0.010	0.010	0.046^{***}	0.013	-0.009	0.016
Squared distance to all-weather road	-0.001^{**}	0.000	-0.001^{***}	0.000	0.000	0.000
Distance to water source (dry season)	-0.049^{***}	0.011	-0.004	0.015	-0.062^{**}	0.027
Squared distance to water source (dry)	0.000^{***}	0.000	0.000	0.000	0.001^{**}	0.000
Distance to water source (wet season)	0.030	0.051	-0.150^{**}	0.068	-0.314^{***}	0.126
Squared distance to water source (wet)	-0.001	0.011	0.027^{**}	0.013	0.044^{*}	0.024
Farmer association	0.185^{***}	0.050	0.320^{***}	0.069	0.623^{***}	0.115
Extension visit	0.542^{***}	0.083	0.769^{***}	0.102	0.888^{***}	0.153
Rural residence	0.408^{***}	0.083	0.428^{***}	0.131	0.370^{**}	0.188
Altitude	0.016	0.011	0.123^{***}	0.013	0.137^{***}	0.015
Region dummies included	*Yes*		*Yes*		*Yes*	

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

Table 4 shows that age, education and gender of the household head are associated with movement away from the non-user class. Specifically, we find that an increase in age of the household head by one year increases the probability of being in the specialized livestock farmers' class and in the intensive diversifiers' class by 4% and 9%, respectively. Yet, inclusion of the squared age term shows a curvilinear relationship, with very old farmers above the average significantly less likely to belong to either class. This result is suggestive of both the farming experience and the innovative behavior aspects: literature on agricultural technology adoption has consistently shown that young farmers are more risk-taking and will likely try out new agricultural technologies. On the other hand, older farmers have more farming experience and will likely switch and manage dealing with new technologies fairly well. Both of these aspects are well reflected in this analysis.

Similarly and consistent with literature, the probability of switching from non-user to other faming classes increases with education; one additional year of education is significantly associated with a 2.5% likelihood of belonging to a specialized livestock farmers class, a nearly 5% likelihood of belonging to a specialized crop farming class, and a massive 13% probability of belonging to a diversified class. We find a negative relationship between use of agricultural technologies and female-headed households. The probability of moving from non-adoption class to specialized livestock farmers, specialized crop farmers or the diversified class, significantly reduces by 22%, 54% or 45%, respectively, when a household is female-headed. This situation is unsustainable since the agricultural labor force is dominated by women, although traditional systems do not fully allow ownership and access to land rights and information to women (Blein *et al*, 2013).

Household size, as a proxy for family labor, positively predicts switching from non-user class to specialized livestock farmer or to diversified class. There is no observed difference between the non-user class and the specialized crop farmer class. An increase in household size by 1 person increases the likelihood of belonging to a specialized livestock farmer class and a diversified farmer class by 7% and 9%, respectively.

Land is an important factor of agricultural production and technology adoption. We find that households with large farm sizes or those with the possibility of getting additional land parcels will most likely switch from non-user class to the other classes. Specifically, results in

Table 4 show that a one acre increase in farm size will raise the probability of belonging to the specialized livestock class or the diversified class by 1.5% and that of belonging to specialized crop farmer class by 1.3%. However, the squared term of farm size shows that the distribution is bell-shaped, implying that additional farm size beyond the population-mean may not necessarily increase the likelihood of class switching. We do not find any convincing evidence of association between land rights and belonging to any of the adopting classes.

Radios and mobile phones are important mediums of agricultural information transmission for rural farmers. In this study, these are some of the key correlates of technology adoption. Households' ownership of radio and mobile phone consistently is associated with the probability of membership into the other three classes relative to the reference class. For example, owning a radio increases the likelihood belonging to a specialized livestock or crop farmer class by more than 40%. Owning mobile phone increases the likelihood of membership in the specialized livestock or crop farming class by over 45% while a marginal effect of 38% is observed for the diversified farmer class.

Turning to locational attributes, we do not find a significant difference between the distance to the nearest market for specialized livestock or crop farmers in reference to the non-user class. However, we find a significant association between distance to nearest market and membership to the diversified class. Specifically, households living far away from markets are more likely to belong to the diversified group in reference to the non-user class. However, the closer the household is to the sub county headquarters, the more likely they will belong to either the specialized crop farmer or the diversified farmer class. As per this analysis, there is no difference in access of all-weather road for specialized livestock farmers and the diversified farmers as compared to the reference class. However, distance is significant for the comparison of specialized crop farmers in reference to non-users: an increase in distance to all-weather roads by 1km reduces the likelihood of belonging to the specialized crop farmer class, implying that most of the farmers in the specialized crop category are rural dwellers. The squared terms of distance to all-weather roads is negative though, indicating that much more rural households with limited access to all-weather roads will possibly not belong to this category or even the specialized livestock category.

Access to water is much more important for diversified farmers as compared to other classes: a 1km increase in the distance to water source reduces the likelihood of the household belonging to the diversified class by 6% in the dry season and by 21% in the wet season. Relatedly, we find a slightly higher likelihood of household's membership to the specialized crop farmer class with respect to water during the rainy season. This somewhat may indicate that diversified farmers are also likely to require water for both their crops and livestock during the rainy and the dry season. Yet, water may seem more important for the specialized crop class during the rainy season. This is suggestive of the fact that most crop farming is rain-fed, heavily dependent on seasonal design with little irrigation done during the dry season. For specialized livestock farmers, water is much more vital during the dry season: a 1km increase in distance significantly reduces the probability of membership to this class by 5% relative to the reference class.

Affiliation to farmer social groups (or associations) as well as visits to demonstration or extension centers is important for information sharing especially regarding new technologies and extension messages. Social groups can also be a good source of credit to finance farm and non-farm operations. Our study shows a strong linkage between social group membership and the three farmer classes in the order of: 62% for diversifiers; 32% for specialized crop farmers and 19% for specialized livestock farmers, with reference to non-users. We find similar trends in the share of farmers that visited extension centers in the year preceding the survey, with the model predicting that households that visited extension service centers have 89% more chance of belonging to the diversifiers group, compared with 77% and 54% for specialized crop and specialized livestock farmers, respectively.

4. Concluding Summary

In this study, we aimed at identifying distinct classes of Ugandan farmers with respect to the commonly used agricultural technologies. We found that improved seed, pesticides, herbicides, and fertilizers were the most commonly used crop technologies. Each of these accounted for a prevalence of more than 10%. For livestock technologies, the use of commercial veterinary drugs was the most prevalent with 30% of farmers using it. Most livestock production systems remain conventional with less than 1% and just 7% of livestock farmers using artificial insemination and improved breeds, respectively. The use of advanced technologies, such as irrigation, animal drought or mechanical traction was a bare minimum among Ugandans. For this reason, subsequent analyses omitted these variables because of insufficient representation.

Using Latent Class Analysis (LCA) methods, the study reveals four distinct classes of farmers as follows: 5% of Ugandan farmers are considered ‘intensive diversifiers’ as they are characterized by using improved crop technologies (improved seed, pesticides and fertilizers) and livestock technologies (commercial veterinary drugs and livestock feed); 14% are considered ‘specialized crop farmers’ because they are characterized by the use of improved crop technologies only (improved seed, pesticides and fertilizers). The third group, labelled ‘specialized livestock farmers’ comprises of about 20% of the farmers and is only characterized by the use of commercial veterinary drugs. The majority of Ugandan farmers (61%) reported non-use of any improved agricultural inputs and are labeled ‘non-users’. In the analysis, we use the non-user class as a reference and examine factors that would possibly drive farmers to join the other three classes.

Using multinomial regression analysis, we find that switching from the non-user class to the intensified diversifiers would be the most difficult to implement. This switch would require that farmers are fairly young but experienced, most preferably an educated male household head operating on a fairly large farm. The switch to intensified diversifiers would also require that households own radio and mobile phones, and are closer to sub-county headquarters possibly for extension information and other relevant technology support. Moreover, intensified diversifiers seem not be reliant on seasonal weather patterns but on irrigation for livestock and crop production, as the switch requires farmers to have access to permanent water sources during the wet and dry seasons. Additionally, being affiliated to social groups probably for informational, technological or financial support from peers is more important for this switch as compared to other classes. Finally, the results show that intensified diversifiers need to have comparatively more access to professional extension services in terms of visits to demonstration sites or physically meeting the extension workers themselves than the rest of the classes.

Switching from the non-user class to the specialized crop farmer class is relatively easier than switching to the intensified diversifiers class but probably more difficult that switching to a specialized livestock farmers class. Switching to a specialized farmers class would require that household heads are male with some level of education. The switch would also be facilitated bt the farm size operated and ownership of telecommunication devices such as a radio and a mobile phone. This switch also requires that households are closer to the subcounty headquarters and not too far away from all-weather roads and water sources, at least during the wet season. This latter requirement indicates that this class of farmers is still dependent on rain-fed agriculture and can only require water for additional irrigation when rains unexpectedly fail during the growing season. Similar to intensified diversifiers, the switch to specialized crop farmers would require access to extension services and social groups, albeit at a lower scale than required for the switch to the intensified diversifiers' class.

Lastly, our results indicate that to switch from non-user class to the specialized livestock class requires that household heads are young, experienced and educated but certainly not to the extent required for the switch to the intensified diversifiers' class. The switch also requires, to a very large extent, that intending households are male-headed. This should not surprise as most livestock-related activities are within the traditional male domain. Farm size is key as well as ownership of radio and mobile phone but not to the extent required for the switch to the other two classes. Households would also need to be closer to all-weather roads and, unlike the specialized crop farmers, to water sources during the dry season. This may imply that livestock farmers are likely only constrained in finding water for their livestock during the dry season. In contrast to crops, livestock can be mobile, able to be moved to water sources in case of temporary deficit as is always the case in the rainy season. Finally, switching from the non-user class to the specialized livestock class would also require agricultural extension support and association to farmer associations, although not to the extent required by specialized crop farmers let alone intensified diversifiers.

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Appendix

Appendix I—Fit statistics for LCA models of technology users

No. of Classes	Likelihood Ratio G^2	AIC	BIC	Adjusted BIC	Entropy	DF
1	5155.6	5167.6	5212.2	5193.2	1	57
2	1268.3	1294.3	1391.0	1349.7	0.622	50
3	606.5	646.5	795.3	731.8	0.777	43
4	**178.7**	**232.7**	**433.6**	**347.8**	**0.73**	**36**
5	149.1	217.1	470.0	362.0	0.645	29
6	61.0	143.0	447.9	317.6	0.764	22

Note. Boldface type indicates the selected model. AIC = Akaike's Information Criterion; BIC = Bayesian Information Criterion.