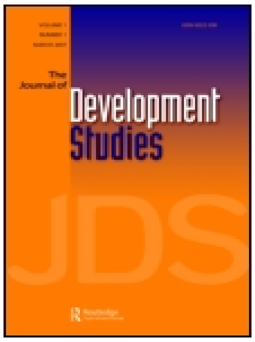

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The Role of Farming Experience on the Adoption of Agricultural Technologies: Evidence from Smallholder Farmers in Uganda

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ABSTRACT *This article investigates the relationship between adoption of and experience with agricultural technologies. We use both non-parametric and parametric estimations on data from rural farmers in Uganda. We find an inverted-U relationship between adoption of and experience with agricultural technologies in banana, coffee and maize. This suggests that farming experience is useful in early stages of adoption of a given technology when farmers are still testing its potential benefits, which later determine its retention or disadoption over time. Thus, gradual advances in technology development and continuous retraining of farmers are essential for sustainable adoption of agricultural technologies for some crops.*

1. Introduction

Whether farming experience enhances or discourages agricultural technology adoption remains unclear in existing studies (Knowler & Bradshaw, 2007). However, definite answers are essential for policy-makers, especially those promoting the adoption of agricultural technologies and participation in field farmer schools (Duveskog, Friis-Hansen, & Taylor, 2011). Field farmer schools have evolved through experiential education for farmers (Feder, Murgai, & Quizon, 2004; Yamazaki & Resosudarmo, 2008). As farmers accumulate experience over time, they progressively switch from traditional agricultural technologies to improved technologies on the basis of observed performance and learning by doing (Arrow, 1962; Dosi, 1982; Feder, Just, & Zilberman, 1985). Learning by doing depends on the release of new agricultural technologies; furthermore, if researchers fail to keep developing superior technologies, these technologies are unlikely to achieve significant progressive adoption (Anderson & Tushman, 1990).

This article offers an in-depth investigation of the relationship between the adoption of and experience with new agricultural technologies. We use panel data from smallholder farmers in Uganda who were trained in a number of technologies to improve agricultural productivity. The findings show that a significant inverted–U relationship exists between the adoption of and experience with agricultural technologies for certain crops but not others.

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An Online Appendix is available for this article which can be accessed via the online version of this journal available at http://dx.doi.org/10.1080/00220388.2014.874556

2. Background on Agricultural Technology Adoption and Farming Experience

Because agricultural production is the most widespread livelihood strategy for most poor rural households in developing countries, particularly in sub-Saharan Africa, development agencies have focussed on the dissemination of improved agricultural technologies to enhance productivity. These technologies broadly include improved crop varieties, land management, and agronomic practices. Development agencies and government programmes often provide farmers with technical knowledge and skills regarding the application of these technologies. However, a number of factors influence the farmers' decision to adopt a certain technology (see, for example, studies cited in Table 1). The determinants of technology adoption can be broadly categorised as resource

Table 1. A sample of studies using farming experience as one of the determinants

Authors	Year	Form of technology adopted	Model used	Location	Sign on ETA	Sign on GFE
Wozniak	1987	Improved cattle feed	probit	Iowa, United States		−*, +^{sqt}
Kebede, Gunjal, and Coffin	1990	Single-ox	logit	Ethiopia		−*/−*st
		Pesticides	logit			+*/ +*st
		Fertiliser	logit			−/ −st
McNamara, Wetzstein, and Douce	1991	Integrated Pest Management	logit	Georgia, United States		−
Adesina and Zinnah	1993	Improved rice varieties	tobit	Sierra Leone	+	
Mariam, Galaty, and Coffin (1993)	1993	Fertiliser	logit	Ethiopia		−*/ +*st
		Pesticides	logit			−/ +*st
		Cross-bred cows	logit			+*/ +*st
		Improved seed	logit			−/ +*st
Caffey and Kazmierczak	1994	Recirculating aquaculture systems	multinominal logit	Louisiana, United States	−	
Saha, Love, and Schwart.	1994	Bovine somatotropin	probit	Texas, United States	+	−
		Bovine somatotropin	OLS		+*	−*
Nkamleu and Adesina	2000	Fertiliser and pesticides	probit	Cameroon		+
Khanna	2001	Soil test technology	probit	United States		+
		variable rate technology	probit			+*
Neill and Lee	2001	Maize-mucuna system	probit		+*	
Holloway, Shankar, and Rahman	2002	HYV rice	probit	Bangladeshi		−
Shiyani, Joshi, Asokan, and Bantilan	2002	Improved chickpea	tobit	Gujarat, India	+	
Staal, Baltenweck, Waithaka, deWolff, and Njoroge	2002	Dairy cattle	probit	Kenya		+*
Herath and Takeya	2003	Intercropping rubber	logit	Sri Lanka	+	
Qaim and de Janvry	2003	Bt cotton	iterated GLS	Argentina	−	
McBride, Short, and El-Osta	2004	Bovine somatotropin	probit	United States		+*
Nkamleu and Manyong	2005	Alley cropping	logit	Cameroon		−
		Improved fallow	logit			+*
Diagne	2006	NERICA rice	poison IV	Côte d'ivoire	+*	
Moser and Barrett	2006	System of rice intensification	tobit	Madagacar	−*, +^{sqt}	
Alene and Manyong	2007	Improved cowpeas varieties	probit	Nigeria	+	
Marenya and Barrett	2007	Stover lines	probit	Western Kenya	+	
		Agroforestry	probit		+	
		Manure	probit		+	
		Inorganic fertiliser	probit		+	
Wendland and Sills	2008	Soybeans	probit	Togo and Benin	+ *	

Notes: ETA = Experience in agricultural technology adoption; GFE = General farming experience; OLS = Ordinary least squares; SUR = Seemingly unrelated regression; IV = Instrumental variable; GLS = Generalised least squares; ^{sqt} = Effect on squared term; st = Sample results for two different sites in the same study. * shows significance level ($p < 0.01$).

endowments (for example, land, labour, livestock and farm equipment); market access (for example, credit and input and output markets); risk and uncertainty (for example, idiosyncratic and covariate shocks); topographic factors (for example, slope, soil type and location); and intellectual capital accumulators (for example, education, experience and extension) (Doss, 2006; Feder et al., 1985; Lee, 2005).

In this article, we focus on the role of intellectual capital accumulators in technology adoption processes. Although both education and extension appear to unambiguously enhance technology adoption (Asfaw & Admassie, 2004; Birkhaeuser, Evenson, & Gershon, 1991; Holloway & Ehui, 2001), the relationship between adoption of agricultural technologies and farming experience remains mixed. Table 1 shows a sample of studies that have included farming experience as a determinant of agricultural technology adoption.

A review of studies in Table 1 identifies two forms of farming experience. First, experience in agricultural technology adoption (ETA), which refers to the time a farmer has spent using an improved technology under consideration. Second, general farming experience (GFE), which refers to the time a farmer has spent in the farming occupation since he/she started making independent production decisions. Table 1 shows that a positive and insignificant relationship between ETA and technology adoption dominates the significant and positive one. By contrast, although a negative and insignificant relationship between GFE and technology adoption appears frequently, there is evidence of both significant negative and positive relationships between technology adoption and GFE. The implication drawn from these studies is that perhaps a non-linear relationship exists between adoption of agricultural technologies and farming experience.

Although the adoption studies listed in Table 1 show mixed relationships between technology adoption and farming experience, in some cases, they come to a common agreement that the mixed relationships may be due to unobserved heterogeneity across farmers. For instance, Marenya and Barrett (2007) found a positive and insignificant relationship between ETA and adoption of soil improvement technologies in Western Kenya. They argue that once household-level factors that change over time are controlled for, experience becomes irrelevant in the adoption process. Wozniak (1987) found a significant and negative relationship between farmer's experience and adoption of improved cattle feed among Iowa (United States) farmers. He argues that experience depreciates faster in a rapidly changing technological environment than in a static one, suggesting that only recent experience is useful in making innovative decisions.

By contrast, Moser and Barrett (2006) found a negative and convex effect of ETA on the adoption of a system of rice intensification (SRI) in Madagascar. They suggest that such an effect reflects high rates of disadoption. However, when they control for farmer-fixed effects, ETA has a significant and positive effect on the adoption of SRI. Although Moser and Barrett recognise that experience may have been correlated with unobserved farmer heterogeneity, they do not show whether more experienced farmers were among the early adopters that later disadopted. Because more experienced farmers adopt new technologies early and switch to other alternatives when they are joined by the late adopters (because of a high opportunity cost for their resources [Feder et al., 1985]). This implies that farmers might have self-selected into SRI adoption.

The agents of agricultural transformation often build on existing traditional agricultural technologies. This suggests that although some technologies may be completely new to the farmers, the complementary practices are not necessarily new. For example, the introduction of a new high yielding crop variety may be incorporated in the existing agronomic practices, it may require adoption of modified agronomic practices (such as wider plant spacing along with row planting), or it may require new practices, such as the use of fertilisers, water harvesting through irrigation, or construction of water diversion channels. In other words, the new technologies are often introduced in packages that include several components (Feder et al., 1985; Leathers & Smale, 1991). Some components of the technology package may be similar to those used in traditional practices; however, they may need to be modified, and can be adopted independently.

Partial or complete adoption of new components of a technology package may follow a sequential pattern based on the level of attributes, including profitability, riskiness, capital requirements, complexity and availability (Byerlee & Hesse de Polanco, 1986; Leathers & Smale, 1991; Nagy & Sanders, 1990). After the farmer has gained experience with already-adopted components, some that meet the required level of these attributes are adopted first and others may be adopted later (Aldana, Foltz, Barham, & Useche, 2011; Leathers & Smale, 1991; Nagy & Sanders, 1990). This implies that some technology packages are divisible, and that this divisibility can lead to dynamic adoption. This is because experience gained through adoption of some of the components provides information about the technology package, which in turn encourages or discourages subsequent adoption. Alternatively, based on the farmer's experience with some of the technology's components, the decision to adopt such components or even the complete technology package may follow a predictable pattern known to the farmer. This is because the outcomes from modified or new practices corresponding to the traditional practices are easily predictable by the farmer. Besides, it is possible that the farmer can access information on outcomes obtained by other farmers already using such technologies. In such a situation, the direct use of farming experience as an explanatory variable in the adoption model may result in biased estimates because of the correlation of experience with the error term. Although we recognise that experience can be treated as a predetermined variable in the adoption model, and hence, as exogenous, it is endogenous in a disadoption model (Wendland & Sills, 2008). Even if experience is treated as a predetermined variable in the adoption model, its contribution to selectivity bias remains. Farmers with prior experience in traditional technologies that are related to the modern technology being disseminated are more likely to self-select into or out of the adoption process depending on the experience with the outcomes from such technologies.

Our study contributes to the existing literature on adoption of agricultural technologies in two ways. First, most adoption studies have relied on the incidence of technology use, and hence employ discrete choice models, or have focussed on the intensity of adoption by using a Tobit model. The latter has largely used farm size allocation to modern technology to measure the intensity of adoption. Instead, we measure the intensity of adoption based on a technology package, where a technology package consists of several components that can be adopted independently and at different periods. Second, a number of adoption studies use farmers' access to extension agents or farmers' participation in agricultural training as one of the determinants of adoption of agricultural technologies. In this study, besides the number of visits by extension agents to farmers, we control for the extension agents' characteristics in the farmers' adoption model.

3. Data Sources and Computation of Adoption Rate

3.1. Data Sources

The data were collected from rural farm households in Uganda by Agricultural Sector Programme Support (ASPS) supported by Danida, which has been supporting smallholder farmers through Farmers' Organisations (FO) in Uganda since 1994. By 2001, FO was operating in 41 districts of Uganda. FO's technical staff train farmers by promoting the adoption of technology packages comprised of several practices (that is, components). Among the trained farmers, highly skilled farmers referred to as extension link farmers (ELFs) are selected to train other farmers.

The ASPS has been conducting impact assessment studies in 12 districts since 2001. We use data from surveys conducted in 2003 and 2005. For the detailed sampling procedure, refer to ASPS (2003). The 2003 survey included a random sample of 142 ELFs and 717 'ELF-trained' farmers, whereas the 2005 survey consisted of 131 ELFs and 706 'ELF-trained' farmers.[1] The raw data include a total of 393 farmers (including ELFs) who participated in both the 2003 and 2005 surveys. Both the 2003 and 2005 surveys considered the same enterprises. These included nine crop enterprises (bananas, maize, rice, coffee, pineapples, oil seed crops, vegetable crops, vanilla and potatoes) and other enterprises included: poultry; zero grazing for dairy cows; piggery; fish farming; and bee-keeping. The sub-sample used in this article is limited to six crop enterprises (bananas, maize, rice, coffee, pineapples and vegetable crops) for three reasons. First, these crop enterprises are considered to be among the top priority enterprises for farmers (ASPS, 2005). Second, a fairly large number of farmers producing these six enterprises were included in both the 2003 and 2005 surveys. Third, apart from the banana enterprise, which had extra dissemination of agricultural practices, the other five enterprises had nearly the same amount of dissemination of agricultural practices. These agricultural practices are described below.

After removing the inconsistencies from the data, we use different observations grouped into two sub-samples. The first sub-sample uses pooled data of 689 farmers participating in these six crop enterprises who were trained by 62 ELFs. A given crop enterprise can appear in different districts, implying that such an enterprise has at least one ELF in the data. More specifically, we analyse each of the six crop enterprises using pooled data for the 2003 and 2005 surveys. The second sub-sample consists of only those farmers who participated in the 2003 and 2005 surveys, where we do a panel data analysis for a combination of all the crop enterprises but the banana enterprise. As previously mentioned, farmers participating in the banana enterprise had more technology components disseminated to them compared to the other five crop enterprises. We conduct a panel data analysis for the banana enterprise separately using a sub-sample of 167 farmers participating in the five enterprises and 83 farmers participating in the banana enterprise. Table 2 reports descriptive statistics for the pooled sub-sample of farmers participating in the six enterprises.

The sub-sample results show that approximately 76 per cent of the trained farmers adopted at least one of the components of the disseminated technologies. The technology components disseminated for all crops included: row planting; crop spacing; fertiliser use; improved crop varieties; pest and disease control; and post-harvest handling. In addition to these technology components, the banana enterprise included additional components: pruning; removal of banana suckers; composting; and soil and water conservation practices.

3.2. Computation of Adoption Rate

The adoption rate was computed as a proportion of the applied components out of the total number of components a farmer was trained in for a given enterprise. ETA was computed as the average number of years for different technology components a farmer adopted for a particular enterprise. The survey considered the effective number of years a farmer used a given technology component; that is, if the farmer used the technology component for three years and later abandoned it, then experience was considered to be three years. If the farmer adopted a technology component and was still using it at the time of the survey, then experience was defined as the number of years from the time of adoption to the time of the survey. For example, if a technology package consists of six components and a farmer adopted two of them, one for three years and another for four years, the average ETA is 3.5 and the adoption rate is 0.33. However, if another farmer adopted only one out of six components for three years, the ETA is 3 and the adoption rate is 0.17. The results show that with an average ETA of approximately four years, the farmers' adoption rate of technology components is approximately 50 per cent on average. The adoption rate for individual crop enterprises are reported in the lower panel of Table 2.

4. Estimation Strategy

The analytical strategy used to explain the relationship between the adoption of agricultural technologies and farming experience is structured in three approaches. The first approach uses a bivariate estimation of technology adoption on ETA, the results of which show the potential relationship between technology adoption and ETA.

The second approach estimates the Tobit model (Tobin, 1958), which allows us not only to estimate the probability that a farmer adopts different components of a given technology package, but also the intensity of adoption rate. We first estimate a simple Tobit model that omits all possible potential explanatory variables except ETA to test the consistency of the relationship established in the first approach. Next, we systematically add other explanatory variables and re-estimate the relation between technology adoption and ETA while observing if the relationship observed in the first approach can be

Table 2. Descriptive statistics

Variable	Entire sample	Non-adopters	Adopters
Farmer characteristics			
Percentage of trained farmers that adopted technology components	75.6		100
Adoption rate of technology components			0.497 (0.239)
Experience in technology adoption (years)			3.7 (2.2)
General farming experience (years)	18.4 (11.5)	19.3 (12.9)	18.2 (11.1)
Percentage of male farmers	50.8**	44.0	53.0
Age of the farmer (years)	43.1 (12.3)	43.0 (13.3)	43.1 (11.9)
Farmer's education (years in school)	7.0 (3.8)	7.0 (3.6)	7.0 (3.9)
Percentage of farmers married	85.1	82.3	85.8
Number of household members engaged in farm activities only	3.2 (2.7)**	3.6 (3.6)	3.1 (2.3)
Number of household members engaged in off-farm activities only	0.5 (1.4)**	0.3 (0.7)	0.5 (1.4)
Percentage of farmers reporting community status as a local leader or teacher	34.3**	28.0	36.3
Percentage of farmers owning a house with brick walls and roofed with iron sheets/tiles	56.6	53.5	57.6
Percentage of famers employed in off-farm activities	25.5	23.8	26.1
Farm size holding (acres)	10.3 (36.3)	11.5 (50.2)	10.0 (30.6)
Distance from home to nearest market (km)	6.5 (7.8)	7.3 (8.2)	6.3 (7.6)
Characteristics of extension link farmer (ELF)			
Percentage of male ELFs	52.1	50.6	52.6
Age of ELF (years)	46.29 (12.02)	44.79 (12.40)	46.79 (11.87)
Experience in technology dissemination	4.4 (2.2)***	3.9 (2.2)	4.7 (2.1)
ELF's education (years in schools)	9.1 (3.3)	9.0 (3.4)	9.2 (3.3)
Percentage of ELFs reporting community status as a leader/teacher	59.5	56.5	60.5
General farming experience (years)	19.3 (10.5)	20.3 (11.0)	19.0 (10.3)
Number of observations (N)	689	168	521
Information collected in 2003 survey only			
Hours of extension visits per season by ELFs	8.7 (8.5)	7.9 (8.1)	9.1 (8.7)
Hours of extension visits per season by government and other NGOs	5.9 (14.9)	5.3 (8.9)	6.2 (17.2)
Percentage of farmers reporting participating in FO training courses	66.0***	54.9	71.8
Number of observations (N)	356	122	234
Enterprise specific adoption rates	**Mean**	**Minimum**	**Maximum**
Banana (N=166)	0.521 (0.267)	0.111	1.00
Pineapples (N=91)	0.466 (0.213)	0.143	0.857
Maize (N=124)	0.512 (0.255)	0.167	1.00
Rice (N=54)	0.429 (0.185)	0.167	1.00
Coffee (N=45)	0.489 (0.197)	0.125	1.00
Vegetables (N=41)	0.522 (0.223)	0.200	1.00

Source: Survey data.
Notes: Significance levels represent values between adopters and non-adopters. ***, **, * show significance level at 1 per cent, 5 per cent and 10 per cent respectively. Figures in parentheses are standard deviations.

rejected. In the second approach, we treat the sample as a pooled cross-section and include all trained farmers, implying that the adoption rate ranges from 0 for non-adoption to 1 for full adoption.

The third approach provides a sensitivity analysis to validate the robustness of the relationships identified in the first and second approaches. This third approach involves a series of estimation strategies that help us to determine the following:

(1) Is the relationship between technology adoption and ETA explained by the observable characteristics or by the unobserved heterogeneity? We use a fixed-effects estimation (Wooldridge, 2010), which controls for both time-invariant and time-varying unobserved (and observable) heterogeneity.
(2) Does this heterogeneity lead to self-selection into FO participation? The details of this sensitivity analysis are described in Section 2 of the Online Appendix.

The general model used to estimate how fixed and time varying observable and unobservable effects influence the household's adoption rate is presented as the following:

$$ADOPT_{kit} = \gamma ETA_{kit} + FMRv_{kit}\beta + ELFv_{j(kit)t}\alpha + FMRc_{ki}\sigma + ELFc_{j(kit)}\rho + \omega_{ki} + \phi_{j(kit)} + \varepsilon_{kit} \quad (1)$$

where $ADOPT_{kit}$ is the adoption rate of enterprise k by farmer i in period t. ETA_{kit} is the variable of interest (that is, experience in technology adoption), and γ is the parameter that defines the relationship between $ADOPT_{kit}$ and ETA_{kit}. $FMRv_{kit}$ and $ELFv_{j(kit)t}$ are vectors of other observable explanatory variables for farmers and ELFs respectively. $j(kit)t$ is a function that links farmer i to enterprise k and ELF j at time t. $FMRv_{kit}$ varies across k, i and t, and $ELFv_{j(kit)t}$ varies across k, j and t. Farmers can switch from one enterprise to another over time, but not the ELFs.[2] $FMRc_{ki}$ and $ELFc_{j(kit)}$ are vectors of time-invariant variables for farmers and ELFs respectively. The unobserved individual effects of farmers and ELFs that are fixed over time are contained in ω_{ki} and $\phi_{j(kit)}$ respectively. β, α, γ and ρ are other parameters to be estimated, and ε_{kit} is the unobserved error term.

Following Wooldridge (1995), Equation (1) can be consistently estimated using a fixed-effects estimation that controls for both observed characteristics ($FMRc_{ki}$ and $ELFc_{j(kit)}$) and unobserved effects (ω_{ki} and $\phi_{j(kit)}$) that may be correlated with the observable factors. The fixed-effects estimation can be used to achieve consistency for the sub-sample of adopters only by assuming that $E(\varepsilon_{kit}) = 0$. This assumption allows for a serial correlation and heteroskedasticity in ε_{kit}, and does not place restrictions on how the decision to adopt agricultural technologies relates to the observed characteristics and the unobserved heterogeneity.

5. Results

This section presents the results estimated using the analytical procedure described in Section 4. We first use a simple bivariate regression to establish the relationship between technology adoption and ETA. Figure 1 reports both semi-parametric and non-parametric estimates of adoption of agricultural technologies plotted against ETA. The use of semi-parametric and non-parametric regressions allows ETA not to exhibit a predetermined distributional form but is shaped according to information derived from the data. The non-parametric regressions in left panel of Figure 1 exhibit a relationship between adoption of agricultural technologies and ETA tending toward an inverted-U curve for bananas, maize and coffee, but this relationship tends to flatten out after attaining an adoption ceiling for pineapple, rice and vegetable enterprises. To test the sensitivity of these relationships to the effects of other farmer characteristics, we use a semi-parametric regression (right panel of Figure 1) following the approach suggested by Lokshin (2006) and Yatchew (1997). The semi-parametric regression combines both parametric and non-parametric specifications, in which the ETA variable and other control variables are entered into the adoption model non-parametrically and parametrically respectively. The parametric variables used are the same as those used in Model VIII in Table 3. The significance test of the ETA variable that is entered into the specification non-parametrically indicates that ETA is highly significant (p-value of 0.000). The semi-parametric regressions produced consistent inverted-U relationship for bananas, maize and coffee. A similar relationship obtained with non-parametric regressions for pineapple and vegetable enterprises is consistent when semi-parametric regressions are used. Nonetheless, the relationship appears to be ambiguous in case of rice enterprise. In the subsequent analyses, we focus on the inverted-U relationship for bananas, maize and coffee enterprises. Further results for pineapples, rice and vegetables are reported in the Online Appendix.

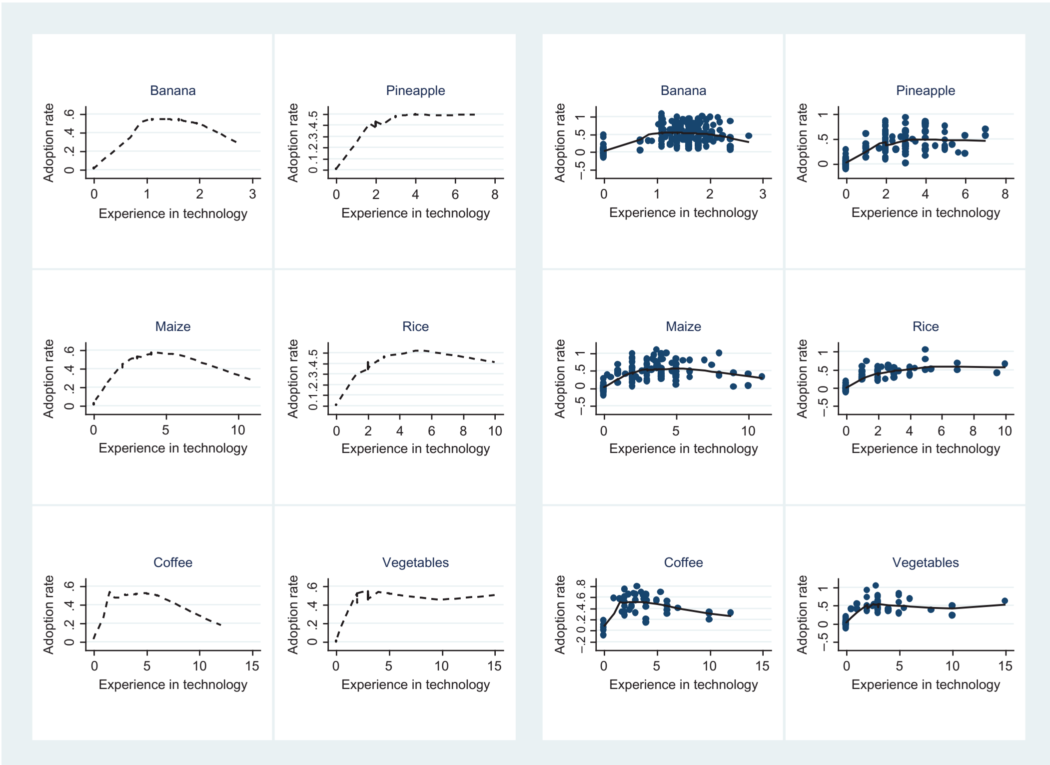

Figure 1. The left panel shows the non-parametric (dashed line) prediction of adoption rate on ETA. The right panel shows semi-parametric prediction of adoption rate ETA. Note that only the ETA for banana enterprise is transformed using logarithms because it was skewed to the left.

Table 3 reports different specifications of adoption rates for the model estimated using the pooled Tobit, where different variables (see Online Appendix Section 1) are added sequentially to control for variation in different observed characteristics of the farmer:

(I) a simple specification of ETA and its quadratic term;
(II) a specification that controls for farmers characteristics;
(III) a specification that controls for wealth effects;
(IV) a specification that controls for both farmer and wealth effects;
(V) a specification that controls for ELF effects;
(VI) a specification that controls for both farmer and ELF effects;
(VII) a specification that controls for wealth and ELF effects;
(VIII) a specification that includes all these effects combined with the distance to the input-output market; and
(IX) a specification that includes all variables in (VIII) plus extension service delivery from ELFs, government, and other non-governmental organisations (NGOs).

However, the last specification (IX) uses only data from the 2003 survey because information on extension visits to the farmers was collected only in the 2003 survey.

Results in Model I show a consistent inverted-U relationship we observe in Figure 1 for bananas, maize and coffee enterprises when we omit all possible explanatory variables except ETA. The same relationship is consistent in all specifications in Table 3. The adoption rate of agricultural technology is lower at lower levels of the farmer's experience with the new technology, but as the farmer gains

Table 3. Tobit estimations of technology adoption and experience in technology adoption (ETA)

Individual enterprises	Model with ETA (I)	Farmer effects (II)	Wealth effects (III)	Farmer and wealth effects combined (IV)	ELF effects (V)	Farmer and ELF effects combined (VI)	Wealth and ELF effects combined (VII)	Farmer, wealth and ELF effects combined (VIII)	Farmer, wealth, ELF and extension effects combined (IX)
Banana (N=211)									
ETA (years)	2.457***	2.525***	2.462***	2.523***	2.413***	2.482***	2.427***	2.488***	13.648***
	(0.265)	(0.261)	(0.265)	(0.261)	(0.263)	(0.260)	(0.264)	(0.260)	(5.125)
ETA squared (years)	–1.087***	–1.132***	–1.090***	–1.131***	–1.068***	–1.113***	–1.077***	–1.117***	–5.703**
	(0.130)	(0.130)	(0.130)	(0.130)	(0.128)	(0.129)	(0.129)	(0.128)	(2.180)
Maize (N=154)									
ETA (years)	0.299***	0.304***	0.301***	0.307***	0.294***	0.299***	0.296***	0.294***	0.597***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.027)	(0.026)	(0.026)	(0.026)	(0.061)
ETA squared (years)	–0.027***	–0.028***	–0.027***	–0.028***	–0.026***	–0.027***	–0.027***	–0.026***	–0.062***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.011)
Coffee (N=51)									
ETA (years)	0.212***	0.212***	0.214***	0.215***	0.182***	0.169***	0.182***	0.176***	0.382***
	(0.040)	(0.039)	(0.040)	(0.039)	(0.041)	(0.037)	(0.041)	(0.038)	(0.059)
ETA squared (years)	–0.018***	–0.018***	–0.018***	–0.019***	–0.016***	–0.015***	–0.016***	–0.016***	–0.043***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.010)

Source: Survey data.
Notes: Explanatory variables included but not shown in the table are listed in the Online Appendix; figures in parentheses are robust standard errors; ***, **, * show significance level at 1 per cent, 5 per cent and 10 per cent respectively. Note that ETA for banana enterprise is transformed using logarithms because it was skewed to the left, but ETA for the rest of other enterprises is not transformed. N is the number of observations. Full results are available on request from authors.

more experience with the technology over time, the adoption rate first increases at a decreasing rate before declining at higher levels of farmer's experience.

In Model II, we include farmer's characteristics to control for possible market imperfections in the labour market (measured through participation in labour markets) and variation in the farmer's ability (reflected through farmer's education, age, and gender). The magnitude of the inverted-U relationship observed in Model I barely changes after controlling for farmer characteristics. Similar effects are observed in Models III through to VIII. After including the effects of extension service delivery in Model IX (that is, the number of contact hours between extension agents and farmers per season), the magnitude of the inverted-U relationship increases substantially.

Model IX uses the 2003 survey data only, whereas Models I to VIII use the pooled data of the 2003 and 2005 surveys. Therefore, a comparison of estimates in Model IX with estimates in Models I to VIII should be conducted cautiously. Despite this caution, extension service delivery appears to explain the inverted-U relationship between technology adoption and ETA more strongly than the other observed farmer characteristics, wealth indicators, ELF characteristics and input–output market access. Considering Model VIII, which controls for different farmer and ELF characteristics, we find that the maximum number of years beyond which the adoption of agricultural technologies declines varies among enterprises. In our sample, the adoption rate of technologies in banana enterprise rises and falls after two years, and does so after approximately six years in maize and coffee enterprises. These turning points do not differ appreciably when we use Model IX, which controls for extension service delivery effects in addition to all other factors in Model VIII.

Despite the evidence of inverted-U relationship between adoption of technologies and ETA observed in bananas, maize and coffee enterprises being consistent when using non-parametric, semi-parametric and parametric specifications, it is worth noting that an inverted-U relationship can be observed even if the true relationship is not. This is the case for the relationships observed in Figure 1 for pineapples, rice and vegetables being inconsistent with inverted-U relationship observed when parametric specification is used (see table A1 in the Online Appendix). Possible explanations for the inconsistent relationships between parametric and non-parametric (and semi-parametric) estimations are, first, the bivariate relationships in Figure 1 do not control for the biases attributed to other omitted variables. Second, missing information on crop-specific farming practices may be responsible for the inconsistent relationships. For example, rice and tomatoes are rarely intercropped with other crops in Uganda, while bananas and coffee are often intercropped with other crops. The intercropping practice may compel some farmers to adopt certain practices. For example, a land constrained farmer, at one point in time, may be forced to practice intercropping in his/her banana plantation, which may result in adoption of pruning and de-suckering practices. But the farmer may gradually discontinue these practices as he/she gains access to more land over time.

Other than ETA, we examined how the adoption rate responds to farmer education and extension service delivery as components of human capital accumulators. The results show that the relationships between the adoption rate and the farmer's education and extension service delivery are unclear across different enterprises (see Figure A1 in the Oonline Appendix). Extension service delivery was measured as the average of contact hours between the farmer and extension agents from government, ELFs and other NGOs.

With respect to education, we experimented with different specifications similar to those reported in Table 3 where both the linear and squared terms of a farmer's education were used as explanatory variables. The results are not reported here, but are available on request. Consistent with Figure A1 (see the Online Appendix), we found a weak significant U-shaped relationship between the adoption rate and a farmer's education (without considering other explanatory variables) in rice and vegetable enterprises. With the exception of the pineapple enterprise, which exhibited a positive but insignificant relationship between the adoption rate and farmer's education (both in its linear and squared terms), all other enterprises indicated insignificant U-shaped relationships between the adoption rate and farmer's education when we included other explanatory variables. When we excluded the squared term of farmer's education, the relationship between the adoption rate and farmer's education was positive and insignificant in all considered enterprises, except for the rice and coffee enterprises. This relationship in rice enterprises was negative but insignificant, whereas the relationship was positive and only significant at the 10 per cent significance level in coffee enterprises.

Overall, although education has been found to enhance adoption of agricultural technologies elsewhere (Doss, 2006), for our sample farmers, we find that education is generally not critical. This finding may be attributed to the fact that highly educated individuals often engage in gainful employment other than agricultural production. Our sample data results confirm this relationship: the correlation coefficient (0.208) between employment in off-farm activities and farmer education is positive and significant at $p < 0.001$.

Regarding the adoption rate and extension service delivery, the results, which are not presented here, indicate that extension service delivery (by ELFs or other agents) significantly enhanced the adoption rate of agricultural technologies in banana and rice enterprises, but significantly reduced the adoption rate in pineapples and rice. The relationship was not significant in maize and coffee enterprises, whereas the relationship was significant and ambiguous in vegetables. Extension service delivery by ELFs reduced adoption rate in vegetable enterprises, whereas extension service delivery by other extension agents enhanced adoption rate.

6. Sensitivity Analysis

To check the robustness of our findings with respect to unobserved heterogeneity across households and self-selection bias into adoption of technologies, we limited the analysis to the sub-sample of farmers that adopted the technology components and were observed in both the 2003 and 2005 surveys. Considering the sub-sample of adopters implies that the dependent variable is no longer censored at zero; we thus opted to use both random- and fixed-effects estimations instead of Tobit ones. The analytical strategy and detailed results are reported in Section 2 of the Online Appendix. Two key results are worth noting in our sensitivity analysis.[3]

First, the inverted-U relationship between adoption of agricultural technologies and ETA is robust even after controlling for observed effects (both time-invariant and time-variant), unobserved heterogeneity at both the farmer and enterprise levels, and farmer selection bias into adoption of agricultural technologies (Model VIII in Table A2,]. The findings indicate that farmers are able to adopt technology components gradually as they gain more experience in the technology: up to one year of ETA in a banana enterprise, and approximately six years of ETA in all other considered enterprises, after which the adoption rate begins to decline. These results suggest that controlling for only observed effects may overestimate the adoption rate for banana enterprise; that is, earlier estimates in Section 5 show that the adoption rate drops after attaining two years of ETA in a banana enterprise.

Nevertheless, our results are further supported by considerable disadoption rates among some farmers. Figure A2 in the Online Appendix reports the disadoption rates of technology components by ELFs and the reasons for disadoption. We were unable to access the information on the disadoption of technology components by all sample farmers. However, because ELFs are trainers of trainees, the results reported in Figure A2 may provide insight on the disadoption of technology components by farmers. The figure shows that high disadoption rates are common in rice (32%), pineapples (31.4%) and coffee (31%), followed by vegetables (27%), bananas (25%) and maize (21%) mainly because of high labour-demanding activities in these crops and limited access to adequate farm size. The latter constraint is mainly associated with technologies that require wide plant spacing, which was a common practice emphasised by the FO in all enterprises.

Second, our sensitivity analysis results confirm the presence of selection bias into adoption of agricultural technologies. The self-selection bias is statistically significant and positive in the estimations of the banana enterprise and that for all enterprises. This implies that the unmeasured effects relating to participation in FOs increase the degree of adoption of technology components; that is, observed and unobserved heterogeneity across farmers and different enterprises (and, to some extent, villages) play a key role in explaining the variation in the adoption rate of technology components.

Overall, even though our sensitivity analysis enabled us to confirm an inverted-U relationship between the adoption rate of agricultural technology components and ETA, this relationship is valid and strong for some crops (in this case bananas, maize and coffee) not all crops. For those crops in which the inverted-U relationship between the adoption rate of agricultural technology components and ETA is definite, it is consistent with the process of adoption–abandonment of technologies (Dinar & Yaron, 1992; Jansen, Walker & Barker, 1990); that is, in early stages of the introduction of a new technology, the adoption rate is low because farmers may have limited information regarding the potential economic benefits and possible risks of the technology. However, as farmers gain experience over time, they acquire more information on the benefits and risks associated with the technology. Then adoption rate increases until it reaches an inflection point, after which it increases at a decreasing rate towards an upper ceiling, beyond which the adoption rate begins to decline gradually until the technology is abandoned. Abandonment can result from falling profitability, declining yields or substitution of technologies (Cameron & Metcalfe, 1987).

Our findings also render support to the theoretical assertion of Arrow (1962) that 'learning is the product of experience', and that there is an equilibrium response pattern for any given technology toward which the behaviour of a learner tends with repeated exposure. In other words, when farmers are exposed to the same technology repeatedly, such technology is subject to diminishing returns. To have a progressively increasing adoption rate, agents or developers of agricultural technologies must then ensure that technologies are gradually advancing rather than duplicating them.

7. Conclusion, Implications and Limitations

Much of the empirical literature on the adoption of agricultural technologies reports mixed relationships between the adoption rate of agricultural technologies and farming experience. This article investigates the relationship between adoption of agricultural technologies and experience in technology adoption. We use both cross-sectional and panel data collected from smallholder farmers in Uganda. The analytical strategy used enables us to control for both time-variant and time-invariant observable effects of the farmer, the farmer- and crop-specific unobserved heterogeneity, and selection bias into the adoption of agricultural technologies.

We find evidence that the relationship between the adoption of agricultural technologies and experience in technology adoption takes the form of an inverted-U shape in bananas, maize and coffee. This finding suggests that farming experience is largely useful in the early stages of adoption of a given technology for some crops, when farmers are still testing its potential benefits. Then, farmers may abandon the technology if the benefits are smaller than the efforts used, especially if the technology is labour demanding and requires an expansion of the farm size. This implies that in addition to gradual advances in technology improvements, continuous retraining of experienced farmers is essential for them to keep updating their farming experiences and to increase the adoption of improved agricultural technologies. This is particularly important in the framework of designing effective policies for widening the adoption of new agricultural technologies.

However, because of data limitations we were unable to determine what motivates farmers to drop a technology (or technology components) after a certain number of years of experience. Some possible reasons may be that farmers fail to achieve their expected benefits from the newly adopted technology, or that the farmers tend to have better alternatives to substitute for the adopted technologies. The other challenge is that an inverted-U relationship between adoption and experience in technology adoption can be observed using different econometric specifications even if the true relationship is not. To overcome this limitation requires detailed historical data on adoption of specific crop practices per farmer. These issues may be addressed in future research, which may also consider an extension of our analytical strategy to test our inverted-U relationship between technology adoption rate and farming experience against curves that tend to asymptote toward a plateau, such as using switching regression models with Mitscherlich regimes (Paris, 1992).

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Notes

1. The impact assessment surveys targeted farmers that were trained by ELFs. However, some of the 'ELF-trained' farmers had previously participated in trainings organised by FO. As argued in Section 4, the analysis is based on participation in FO to control for selection bias.
2. ELFs are localised in communities where they live with their fellow farmers. Farmers in a given community have access to one ELF that may offer extension work on more than one enterprise. However, an ELF in a given community can be replaced with another one who still offers the same extension work like the former one. Although one may argue that an ELF replacement may come with different skills and other attributes, replacement of ELFs does not exist in our sample.
3. The sensitivity analysis involved three levels of panel data analyses. First, an analysis involving banana enterprise alone. Second, an analysis involving all enterprises considered in this study except banana enterprise. The details of the first and second analyses are reported in the Online Appendix. Third, an analysis involving maize and coffee enterprises combined to test whether the inverted-U relationship observed in Figure 1 and Table 3 is robust to unobserved heterogeneity. The analytical strategy follows the one described in the Online Appendix. Although some models could not run due limited number of observations, for those that were able to run, the inverted-U relationship remained consistent even after controlling for unobserved heterogeneity. The results are not reported but available on request.

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