African Journal of Agricultural and Resource Economics Volume 10 Number 2 pages 117-130

The role of gender in fertiliser adoption in Uganda

Gracious M. Diiro*
Department of Agribusiness & Natural Resource Economics, Makerere University, Kampala, Uganda. E-mail: diirog@yahoo.co.uk

Alan P. Ker
Department of Food, Agricultural & Resource Economics, University of Guelph, Guelph, Ontario, Canada. E-mail: aker@uoguelph.ca

Abdoul G. Sam
Department of Agricultural, Environment, & Development Economics, The Ohio State University, Columbus Ohio, USA. E-mail: sam.7@osu.edu

*Corresponding author; authors listed alphabetically

Abstract

Although Uganda has poor soils with low organic matter, fertiliser is not widely adopted, especially by female-headed households. Thus we examine the role of gender in inorganic fertiliser adoption using a national household survey. We estimate separate models for female- and male-headed households to ascertain if the drivers of adoption differ by gender. With respect to male-headed households, we find the number of extension visits, age of head of household, and non-farm earnings significant, but education and distance to market insignificant. With respect to female-headed households, we find education and distance to market significant, but the number of extension visits, age of head of household and non-farm earnings insignificant. Our results are robust in that they hold using parametric as well as semiparametric single index models. These findings suggest that different policies may be needed to incentivise fertiliser adoption by male- and female-headed households.

Key words: role of gender; fertiliser adoption; single-index models; Uganda

1. Introduction

Uganda's economic growth is hampered by low productivity of the agriculture sector, estimated at only 2% compared to the 6% government-set growth target (Uganda Bureau of Statistics 2010).[1] Poor soils and scarce use of modern technologies are some of the major causes of low yields. Furthermore, there is evidence of massive soil fertility depletion due to increasing population density.[2] Henao and Banaante (2006) estimate that soils in Uganda lose about 66 kg of nitrogen (N), phosphorus (P) and potassium (K) per hectare annually, making it one of the highest rates of soil nutrient depletion in Sub-Saharan Africa (SSA). Moreover, the cost of replenishing the depleted soil nutrients is high, averaging roughly 20% of household income (Nkonya *et al*. 2005).

Inorganic fertiliser has the potential to sustainably raise crop productivity and enhance the food security and incomes of households. A number of studies have argued that limited fertiliser use has

[1] The sector contributes at least 40% of the national GDP and about 85% of the export earnings. Additionally, agriculture employs over 70% of the national labour force (Government of Uganda, 2009).
[2] Population pressure leads to land degradation because land scarcity forces farmers to cultivate the same land every season, as well as to reclaim marginal land areas such as wetlands.

impeded meaningful agricultural productivity gains in SSA countries (Larson & Frisvold 1996; Morris *et al*. 2007; Druilhe & Barreiro-Hurle 2012). The results from field trials conducted by Sasakawa Global 2000 show that the application of fertiliser (at a rate of 90:40 kg per hectare of nitrogen and phosphorus) to maize yields 4 312 to 6 054 kg per hectare compared to the 550 kg per hectare for farmers who do not use fertilisers.[3] In addition, the use of fertiliser can significantly enhance the effectiveness of other agricultural technologies by boosting plant nutrients (Larson & Frisvold 1996). Despite these proven beneficial effects of fertilisers, its use in SSA countries continues to lag far behind other developing countries, where the intensification of production agriculture has been accompanied by a considerable increase in fertiliser application.[4] In Uganda in particular, both the fraction of farmers using fertiliser and the intensity of fertiliser application are quite low. Yamano and Arai (2010) found that only 7 to 8% of Ugandan farmers used fertilisers in 2009, compared to about 17 to 31% reported by Suri (2011) in neighbouring Kenya. In addition, an average farmer in Uganda applies about 2.1 kg per hectare, far below the 32.4 kg per hectare used by a farmer in Kenya (World Bank 2013). Alternative sources of soil nutrients, such as manure and crop residues, are labour intensive and require large quantities to attain adequate nutrient levels (Morris *et al*. 2007). For instance, a farmer may need to apply about six to 10 tons of manure per hectare to generate adequate levels of nitrogen and phosphorous (Abdoulaye & Sanders 2005).

Several explanations for low fertiliser use have been advanced by economists. Reardon *et al*. (1999), Kelly (2006) and Benson *et al*. (2013) suggest that farmers are uncertain of the returns from fertiliser due to price volatility and other source of risk, such as pests and diseases whose joint distribution with fertiliser is unknown. Abdoulaye and Sanders (2005), Kelly (2006) and Morris *et al*. (2007) suggest that farmers lack adequate knowledge and skills in using fertilisers. Asfaw and Admassie (2004), Yamano and Arai (2010) and Duflo *et al.* (2008) report that literacy/ formal schooling and agricultural extension increase fertiliser adoption because they enhance a farmer's technological awareness. Deterrents to fertiliser adoption are high costs, poor transportation networks, limited and untimely supply of fertilisers, and liquidity/credit constraints (Abrar *et al.* 2004; Yamano & Arai, 2010). Indeed, Yamano and Arai (2010) and Duflo *et al*. (2008) find that many subsistence farmers want to apply fertilisers but do not have liquid capital to purchase them.[5] Some studies, such as Reardon *et al*. (2007) and Barrett *et al*. (2001), have found that income from non-farm activities assists in overcoming liquidity and credit constraints. Similarly, Duflo *et al*. (2011) conclude that offering small price incentives aligned with farmers' cash flow cycles can increase the use of fertiliser substantially.

While a number of studies have analysed fertiliser use in many developing countries, empirical work on fertiliser adoption in Uganda is scarce. We are only aware of one study, by Okoboi and Barungi (2012), which found that farmers do not use fertilisers primarily because of a lack of liquidity and knowledge of the use of fertilisers. Our study uses a more recent, nationally representative dataset collected by the Uganda National Bureau of Statistics in 2010 and contributes to the existing literature on adoption by delving further into the effect of gender. That is, we estimate separate adoption models for male- and female-headed households to determine if the drivers of adoption differ between the two categories of households.

The role of gender in the adoption of agricultural technologies in Africa has been explored in a number of studies. For example, Doss and Morris (2001) found that female farmers in female-

[3] Sasakawa Global 2000 is a programme that aims to build the capacity of smallholder farmers to improve their livelihoods through the adoption of modern farming methods, including the use of quality seed and small amounts of fertiliser. In Uganda, Sasakawa Global 2000 has been active since 1997, covering over 24 districts in the country.
[4] According to data in Druilhe and Barreiro-Hurle (2012), SSA farmers applied on average 7.1 kg of fertiliser per ha of arable cropland compared to 129.4 in South Asia and 104.8 in Latin America over the period 2006 to 2008.
[5] In their study, Duflo *et al.* (2011) found that the proportion of farmers using fertiliser increased by at least 33% when farmers were offered the option to buy fertiliser immediately after harvest.

headed households in Ghana were less likely to adopt modern varieties and fertiliser than female farmers in male-headed households. Chirwa (2005) found that gender was not significant for both fertiliser and hybrid seed adoption in Malawi. However, the number of observations was relatively small (N = 202). Isham (2002) also did not find gender to matter for fertiliser adoption in Tanzania, again with a relatively small sample (central plateau region (297), plains region (142)). Ndiritu *et al.* (2011) looked at adoption of agricultural technologies in Kenya. With respect to fertiliser, they found that female-headed households' interaction with extension visits was significant. The interaction coefficient was negative, suggesting these visits decrease the probability of adoption by female-headed households.

None of the above studies estimated separate models for male- and female-headed households to determine if the drivers that effect adoption differ by gender. According to a recent World Bank (2014) report, women constitute almost half of the agricultural workforce in SSA countries. Yet there is a well-documented gender gap in productivity between male- and female-managed farm plots. For example, Kilic *et al.* (2013) estimated a 25% productivity gap in favour of male-managed plots in Malawi. Furthermore, using the Blinder-Oaxaca decomposition, they found that much of the gap is explained by differences in inorganic fertiliser use and the share of cultivated land devoted to crop exports. The 2011 State of Food and Agriculture (SOFA 2011) report estimates that closing the gender productivity gap could shrink the number of undernourished people by between 100 and 150 million.

The manuscript proceeds in the following manner. Sections two and three discuss the economic model and empirical methodologies respectively. Section four discusses our data. Section five presents the empirical results, while the final section summarises our findings and discusses policy implications.

2. Economic model

We studied the fertiliser adoption behaviour of smallholder farmers in Uganda using the conventional random utility framework (Hausman & Wise 1978). It is assumed that households make rational production decisions and therefore only apply fertiliser if doing so maximises their expected utility. Households are faced with two production technologies: one with fertiliser and one without. Following previous research (Hanemann 1984; Baltasa & Doyle 2001), the random utility function for a farm household facing the technology set can be specified as

$$\boldsymbol{\pi_{ik} = \bar{\pi}(s_{ik}, \tau_i) + \epsilon(s_{ik}, \tau_i) = x_{ik}\beta + \epsilon_{ik}, i = 1, 2, \ldots n}, \quad (1)$$

where $\boldsymbol{\pi_{ik}}$ denotes expected utility a farmer derives from fertiliser technology k ($k = 1$ if fertiliser is applied, $k = 0$ otherwise); $\boldsymbol{\bar{\pi}(s_{ik}, \tau_i)}$ is the deterministic component of the utility function specified as a function of the observed attributes of the technology options ($\boldsymbol{s_{ik}}$) and the socio-economic description of a household ($\boldsymbol{\tau_i}$); $\boldsymbol{\epsilon(s_{ik}, \tau_i)}$ is the stochastic component of the utility function representing the idiosyncrasies specific to each farmer, as well as unobserved attributes affecting technology choice, and measurement errors; $\boldsymbol{x_{ik}}$ represents the covariates $\boldsymbol{s_{ik}}$; and β is the vector of parameters. Given the specification of $\boldsymbol{\pi_{ik}}$, a utility maximising farm household would choose to apply inorganic fertiliser if the corresponding expected utility is higher than that generated from the traditional technology (no fertiliser), i.e. if $\boldsymbol{\pi_{i1} > \pi_{i0}}$. The binary choice single-index model of fertiliser adoption is thus specified as

$$\boldsymbol{y_i = I\{\pi i1 \ > \ \pi i0\} = I\{x_{i1}\beta + \epsilon_{i1} - x_{i0}\beta - \epsilon_{i0} > 0\} = I\{x_i\beta + u_i\}}, \quad (2)$$

where $\boldsymbol{u_i} = \boldsymbol{\epsilon_{i1} - \epsilon_{i0}}$ is the random error term with zero mean, and the coefficient vector β is defined up to some scalar normalisation.

3. Empirical methods

The applied literature is dominated by a parametric estimation of binary choice models, where the cumulative distribution function (cdf) of u_i is assumed to be normal or logistic. If the error term distribution is normal (logistic), then the parameter vector can be consistently and efficiently estimated with a probit (logit) model. The probit model is the model of choice in the literature on agricultural technology adoption. Practically, $\hat{\boldsymbol{\beta}}$ is chosen by maximising the likelihood function

$$\boldsymbol{L(\beta) = \sum_{i=1}^{n} y_i \log(\Phi(x_i\beta)) + (1 - y_i) log(1 - \Phi(x_i\beta))}, \tag{3}$$

where Φ() is the normal cdf.

In addition to the probit model, we considered an alternative semiparametric specification of the single-index model that is robust to distributional misspecification. There has been significant research on the semiparametric estimation of single-index models (e.g. Ichimura 1993; Klein & Spady 1993; Horowitz & Hardle 1996; Ergun *et al.* 2011). Next, we briefly outline the model developed by Klein and Spady (1993).

The single-index model above implies that

$$\boldsymbol{P\,(y = 1|x) = E(y|x) = F\,(x\beta)}, \tag{4}$$

where $\boldsymbol{F}$ is an unknown function called the *link* function and $\boldsymbol{x\beta}$ is the *index*. Among the advantages of single-index models is dimension reduction. The index $\boldsymbol{x\beta}$ is a scalar, and thus single-index models do not suffer from the curse of dimensionality; if $\boldsymbol{\beta}$ were known it would be possible to estimate $\boldsymbol{F}$ as the nonparametric mean regression function of $\boldsymbol{y_i}$ on $\boldsymbol{z_i = x_i\beta}$, which is a scalar. Therefore, in single-index models it is possible to estimate $\boldsymbol{F}$ at the nonparametric rate as if there is a single regressor, and the coefficient vector $\boldsymbol{\beta}$ at the parametric rate ($O(n-1/2)$) (Klein & Spady 1993).

Unlike the probit and logit, the Klein and Spady (1993) estimator (henceforth KS) does not rely on any assumption about the distribution of the error term; instead, it estimates the distribution function non-parametrically using kernels. As such, the KS estimator is consistent regardless of the true error distribution. Briefly, the KS estimator of $\boldsymbol{\beta}$ is obtained by maximising the quasi-likelihood function

$$\boldsymbol{l(\beta) = \sum_{i=1}^{n} y_i \log(\hat{F}(x_i\beta)) + (1 - y_i) log(1 - \hat{F}(x_i\beta))} \tag{5}$$

with respect to β, where

$$\boldsymbol{\hat{F}(x_i\beta) = \sum_{j\neq i} y_j K_h(x_i\beta - x_j\beta) / \sum_{j\neq i} K_h(x_i\beta - x_j\beta)}. \tag{6}$$

$K_h(u) = 1/h*K(u/h)$ is the kernel function (usually a symmetric density function) and $h = h(n)$ is the smoothing parameter, such that $h \to 0$ as $n \to \infty$, satisfying the condition $n-1/6 < h < n-1/8$ (condition C8 of Klein & Spady 1993). Klein and Spady (1993) show that $\hat{\beta}$ is consistent and $\sqrt{n}(\hat{\beta} - \beta_0) \to N(0, \Omega^{-1})$, where Ω can consistently be estimated as

$$\hat{\Omega} = \boldsymbol{\frac{1}{n}\sum_{i=1}^{n} \left[\frac{\partial}{\partial\hat{\beta}} \hat{F}\left(x_i\hat{\beta}\right)\right] \left[\frac{\partial}{\partial\hat{\beta}} \hat{F}\left(x_i\hat{\beta}\right)\right]' \left[\frac{1}{\hat{F}(x_i\hat{\beta})(1-\hat{F}(x_i\hat{\beta}))}\right]}. \tag{7}$$

Similar to the probit, a location-scale normalisation is needed to ensure the identification of the parameter vector. For the probit, the location-scale normalisation requires setting the first and second moments of the error term to zero and one respectively. For the KS estimator, the location-scale normalisation is imposed by constraining the intercept to zero and one of the coefficients on continuous regressors to a constant. In addition, and unlike the probit, the KS estimator is consistent even if the errors are heteroscedastic, provided that the heteroscedasticity depends on the regressors only via the index, or is of a known general form. This feature of the KS estimator is particularly attractive in empirical settings where cross-sectional household datasets are used.[6]

4. Data

The data comes from the 2009/2010 Uganda National Household Surveys (UNHS), a longitudinal survey of households in Uganda. The sample consists of 1 912 farmer households. The proportion of farmers (in this sample) who applied fertilisers was only about 5%, which makes it relevant to analyse the factors hindering adoption of the input.[7]

A statistical summary of the variables included in the model is provided in Table 1. They are drawn from the empirical literature on agricultural technology adoption in developing countries. First, it has been noted that subsistence farmers want to use advanced farm technologies, but do not have liquid capital to purchase them (e.g. Duflo *et al*. 2008). These farmers have limited access to credit because markets for credit and insurance are either not available or dysfunctional (Gruhn & Rashid 2001). Where credit markets are available, these institutions are reluctant to provide credit to risky agricultural enterprises (Gordon 2000). Moreover, typical subsistence farmers usually are not able to save their farm earnings to purchase inputs later because they face several other needs that compete for the limited financial resources. We therefore include non-farm income as a control variable to explore if it is used by credit-constrained farmers as an alternative financing mechanism to purchase fertiliser.

[6] To implement the KS estimator, we wrote our own code using a nonlinear optimisation subroutine by quasi-Newton method – the subroutine nlpqn of SAS/IML – to maximise the quasi-maximum likelihood function with respect to the model parameters and the smoothing parameter.

[7] While the percentage of households adopting fertiliser is small, it is consistent with what Okoboi and Barungi (2012) found in their study using the Uganda agriculture census data, and underscores the importance of analysing fertiliser adoption.

Table 1: Summary statistics of the variables by fertiliser adoption and gender

	Adopters		Non-adopters			
Male farmer	Mean	Std. dev.	Mean	Std. dev.	T-stat	P value
Farm size (hectares)	1.36	1.46	1.05	1.34	1.81	0.07
Household size (no. of persons)	7.85	3.83	7.01	3.1	1.86	0.07
No. of extension visits	1.53	4.2	0.48	2.28	2.15	0.03
Age of head of household (years)	43.12	13.09	45.84	14.47	-1.74	0.08
Average education of household	5.42	4.37	4.79	5.05	1.20	0.23
Non-farm income (US$)	723.32	1 583.5	403.92	1 430.31	1.70	0.09
Distance to trading centre (km)	2.77	2.78	4.3	7.82	-3.93	0.00
Eastern region	0.36	0.48	0.18	0.48	3.13	0.00
Central region	0.33	0.47	0.27	0.44	1.17	0.25
Western region	0.24	0.43	0.26	0.44	-0.43	0.66
Northern region	0.07	0.25	0.29	0.45	-7.01	0.00
Female farmer	Mean	Std. dev.	Mean	Std. dev.	T-stat	P value
Farm size (hectares)	1.37	1.3	0.872	1.177	1.30	0.21
Household size (no. of persons)	7.25	2.6	5.705	2.891	2.03	0.07
No. of extension visits	0.42	0.79	0.183	0.828	1.01	0.33
Age of head of household (years)	55.58	12.43	52.545	15.341	0.83	0.42
Average education of household	7.71	5.75	3.496	5.083	2.51	0.03
Non-farm income (US$)	621.82	1 066.26	471.784	2 072.796	0.47	0.65
Distance to trading centre (KM)	0.58	0.51	0.238	0.426	-4.29	0.00
Eastern region	0.25	0.45	0.21	0.41	0.27	0.78
Central region	0.08	0.29	0.322	0.468	2.30	0.04
Western region	0.08	0.29	0.227	0.419	-2.70	0.01
Northern region	1.52	1.93	4.316	7.858	-1.69	0.12

We also included in our model the average education of the household (mean of formal years of schooling of household members aged at least 15) and age of the household head to capture the effects of human capital and risk tolerance (age) on technology adoption. Household size (number of members 15 years or older) was included to control for labour supply for agricultural activities. We controlled for the effects of household access to agricultural markets using the distance from the household to the closest trading centre. Distance is expected to inversely affect the probability of fertiliser adoption through its positive effects on the cost of transportation and thus the effective price of fertiliser. We controlled for farm size to capture benefits of purchasing economies on fertiliser adoption; farmers with larger plots may leverage the size of their plot to obtain lower fertiliser prices. Heterogeneous effects of adoption arising from location and agro-ecological characteristics were captured using regional dummies (the northern, central, western and eastern parts). Differences due to agro-ecological zones may influence fertiliser adoption decisions through their effect on farmers' perceptions of soil quality and yield response. We also identified whether a household was male or female headed, which allowed us to estimate separate models for each.[8]

With respect to male farmers, we found no statistical difference in education between adopters and non-adopters (Table 1). We did find that farm size, household size, number of extension visits and non-farm income were statistically greater for adopters, whereas age and distance to market were statistically greater for non-adopters. With respect to female farmers, we found no statistical difference in the means between adopters and non-adopters for farm size, number of extension

[8] Other variables that could serve as additional controls include fertiliser and crop prices and land tenure. Unfortunately we did not have reliable data on these variables. We noted from the empirical literature that land tenure security may have an effect on adoption decisions regarding long-term land-related investments in the form of soil conservation structure and parcel boundary demarcations, agro-forestry practices (e.g. Soule *et al*. 2000; Hagos 2012). We thus argue that our results may not be biased because fertilisers are a short-term investment and are less likely to be correlated with land tenure. We further note that, in the case of fertiliser and crop prices, they are unlikely to exhibit significant variation over a one-year period.

visits, age and non-farm income. Conversely, household size, education and distance to market were statistically greater for adopters. For fertiliser adopters we found no statistical difference in the means between male- and female-headed households for farm size, household size, education and non-farm income. We did find that the number of extension visits and distance to market were statistically greater for male-headed households, whereas age was statistically greater for female-headed households. With respect to non-adopters, we found no statistical difference in the means between male- and female-headed households for non-farm income and distance to market. We did find that the farm size, household size, number of extension visits and education were statistically greater for male-headed households, whereas age remained statistically greater for female-headed households.

5. Results

As mentioned above, a location-scale restriction is required for the KS estimator. The location restriction is satisfied by excluding the intercept, and the scale restriction is satisfied by normalising the coefficient on household size to the corresponding probit estimate in order to facilitate a comparison of the results. We estimated the optimal smoothing parameter simultaneously with the parameter vector.

We started by estimating a pooled adoption model with gender simply as a dummy variable, as is customary. Table 2 presents the coefficient estimates and their standard errors for the two specifications. The results are robust across both methods and point to a number of significant predictors of fertiliser adoption in Uganda. Estimated coefficients for extension visits, age of the household head, gender of the household head and non-farm income carried the expected signs and were statistically significant in both specifications. Distance to market carried the expected (negative) sign, but was significant only in the probit. The likelihood of fertiliser adoption decreased with the age of the household head. This effect can be explained by the risk aversion of older farmers due to uncertainty in returns on fertiliser adoption (Reardon *et al*., 1999; Kelly, 2006). Experimental studies, such as those by Yesuf and Bluffstone (2007) in Ethiopia, have found that farmers become more risk averse as they age. Consistent with prior studies – Nkonya *et al*. (2005) in Tanzania and Abdoulaye and Sanders (2005) in Niger – the results show that the probability of adoption increases significantly with the number of interactions between the farmer and the agricultural extension agents. Agricultural extension and advisory services are important in enhancing a farmer's knowledge of and skills in fertiliser application. We also noted that the coefficients for the western and northern region dummies were negative and significant. Fertiliser use was low in western Uganda because the farming system was dominated by cattle rearing and banana production, for which fertiliser application is less important. The low use of chemical fertiliser in northern Uganda could be due to the civil strife that has plagued the region for the last two decades.

Table 2: Determinants of fertiliser adoption in Uganda (pooled model)

Variable	Probit model	KS model
Farm size (hectares)	0.0462	0.0479
	(0.0351)	(0.0557)
ln(distance to trading centre (km))	-0.1293*	-0.1324
	(0.0709)	(0.0861)
No. of extension visits	0.0434***	0.0420*
	(0.0157)	(0.0251)
Age of head of household (years)	-0.0077*	-0.0085**
	(0.0041)	(0.0037)
Average education of household (years)	0.0096	0.0094
	(0.0102)	(0.0143)
ln(non-farm income (US$))	0.0618***	0.0593**
	(0.0227)	(0.0271)
Central region	-0.0558	-0.0520
	(0.1350)	(0.1949)
Western region	-0.2680*	-0.2694
	(0.1502)	(0.1934)
Northern region	-0.8313***	-0.8425***
	(0.1971)	(0.2080)
Household size (no. of persons)	0.0233	0.0233
	(0.0172)	(N/A)
Gender of farmer (1 = male, 0 = female)	0.3719***	0.3708***
	(0.1454)	(0.1541)
Intercept	-1.8064***	N/A
	(0.2978)	
F value/Chi square value	76.7300***	N/A
Log likelihood (LL)	-315.4530	-314.9990

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We found that the probability of adoption of fertilisers increased with non-farm income, as expected, suggesting that non-farm activities are an important source of liquid capital for investing in fertilisers. This finding corroborates previous research, which found that diversification into non-farm income activities is an important strategy used by credit-constrained households in developing countries to obtain the capital needed for investment in agricultural technologies (Barrett *et al.* 2001; De Janvry & Sadoulet 2001; Reardon *et al.* 2007; Iiyama *et al.* 2008; Diiro & Sam, 2015). Finally, we noted that male farmers were significantly more likely to adopt fertiliser than female farmers.[9]

The pooled model does not allow us to ascertain if the determinants of adoption differ between male- and female headed households. Drivers may differ for a number of reasons. First, there is evidence that female-headed households in developing countries are, on average, financially worse off (see, e.g., Buvinić & Gupta 1997; Aliber 2003) than male-headed households and thus have more binding constraints on technology investment given the limited access to farm credit (for men and women).[10] Second, female-headed households may be less prone to adopt fertiliser on account of fewer visits from extension agents. According to our summary statistics, for example, female heads received 0.48 visits on average compared to 1.53 for male heads among adopters. Similarly, among non-adopters the corresponding numbers are 0.18 and 0.48 visits for female- and male-headed households respectively. Given the significant effect of extension visits in Table 2, this discrepancy in access to potentially crucial extension information may translate into lower fertiliser

[9] The higher adoption rate of fertiliser by male heads could be the result of more fertiliser-hungry crops being planted by men; unfortunately our data does not allow us to control for the types of crops grown by farmers.

[10] We note, however, that when it comes to non-farm income, female and male heads in our Uganda dataset have comparable resources (see Table 1). Furthermore, Appleton (1996) finds that female-headed Ugandan households are not significantly poorer than their male counterparts, based on a nationally representative dataset.

adoption among female farmers. In the light of these potential differences in motives for technology adoption, we estimate separate models for male- and female-headed households.[11]

Table 3: Determinants of fertiliser adoption by male farmers in Uganda

Male-headed household	Probit model	KS model
Farm size (hectares)	0.0430	0.0541
	(0.0395)	(0.0555)
ln(distance to trading Centre (km))	-0.0786	-0.0838
	(0.0768)	(0.0975)
No. of extension visits	0.0473***	0.0595***
	(0.0159)	(0.0191)
Age of head of household (years)	-0.0111**	-0.0103***
	(0.0047)	(0.0045)
Average education of household (years)	0.0006	-0.0048
	(0.0121)	(0.0165)
ln(non-farm income (US$))	0.0629**	0.0716***
	(0.0247)	(0.0298)
Central region	-0.1858	-0.2240
	(0.1506)	(0.2244)
Western region	-0.2910*	-0.3622
	(0.1636)	(0.2342)
Northern region	-0.9420***	-1.0397***
	(0.2168)	(0.2091)
Household size (no. of persons)	0.0231	0.0231
	(0.0191)	(N/A)
Intercept	-1.2386***	N/A
	(0.2859)	
F value/Chi square value	55.6400***	N/A
Log likelihood (LL)	-262.2334	-44.7227

The coefficient estimates and standard errors are displayed in Table 3 for male-headed households and in Table 4 for female-headed households. For male-headed households, we found the number of extension visits and non-farm income to be positive and significant, whereas the age of the head of the household was negative and significant, as in the pooled model. We did not find a statistically significant effect for farm size, distance to market, household size or education. The results are markedly different for female-headed households in that distance to market, which was insignificant for male-headed households, was negative and significant. Similarly, education was insignificant for male-headed households, but positive and significant for female-headed households. Although extension visits, non-farm income and age of head of household were significant for male-headed households, they were not significant for female-headed households. For both male- and female-headed households, farm size and household size were insignificant. These results, which were robust across the econometric methodologies, are not directly comparable to the literature, as we have seen no research that estimates separate adoption equations by gender in Uganda.

[11] The dependent variable is prone to measurement error in the sense that the dependent dummy variable captures the biological distinction between male and female heads, but may not perfectly capture intra-household decision-making. For example, the husband and wife could make decisions jointly, or decisions could be made by the wife even though the household head is male. Dependent variable measurement error, however, affects only the efficiency, but not the consistency, of our estimates (see, e.g., Carrión-Flores *et al.* 2013).

Table 4: Determinants of fertiliser adoption by female farmers in Uganda

Variable	Probit model	KS model
Farm size (hectares)	0.1130	0.1278
	(0.0863)	(0.1262)
ln(distance to trading centre (km))	-0.4231*	-0.4665**
	(0.2232)	(0.2294)
No. of extension visits	0.0073	0.0121
	(0.1235)	(0.1786)
Age of head of household (years)	0.0044	0.0104
	(0.0099)	(0.0068)
Average education of household (years)	0.0373*	0.0445*
	(0.0207)	(0.0250)
ln(non-farm income (US$))	0.0667	0.0725
	(0.0666)	(0.0563)
Central region	0.5417	0.5977
	(0.3587)	(0.3775)
Western region	-0.2894	-0.2794
	(0.4727)	(0.4967)
Northern region	-0.3232	-0.3062
	(0.5031)	(0.4658)
Household size (no. of persons)	0.0215	N/A
	(0.0463)	
Intercept	-2.7121***	N/A
	(0.7808)	
F value/Chi square value	23.0700***	N/A
Log likelihood (LL)	-46.3410	-44.7227

To gain insight into the magnitude of our estimated effects, Table 5 presents the percentage marginal effects of covariates that are significant in either Table 3 or Table 4.[12] In the top panel we find that, on average, male heads are between 49.3% and 70.4% more likely to adopt inorganic fertiliser than female heads, depending on the econometric specification. The results for male-headed households (middle panel) indicate that, on average, an additional extension visit increases the likelihood of adoption by between 7.2% and 8.7%, and a percentage increase in non-farm income increases the likelihood of adoption by about 0.1%. Regarding female-headed households, we found that a 1% reduction in the distance to market increased the likelihood of adoption by between 0.67% and 0.83%. Given the average distance to market of 4.32 km for female non-adopters, this marginal effect translates into an increase of 15.6% in the likelihood of fertiliser adoption (per the semiparametric model) for a one kilometre reduction (23.18%) in the distance to output market. An additional year of education raises the likelihood of adoption by between 6.4% and 7.3% for female-headed households. Given the average education of 3.5 years for non-adopting female-headed households, the education marginal effect implies that raising the average education level to completion of primary school (six years) would spur a low-end estimate of a 16% increase in the likelihood of adoption among female-headed households.

[12] The percentage marginal effects are the marginal effects expressed as a percentage of the baseline fertiliser adoption rate for male- and female-headed households respectively, in other words it is the marginal effects divided by the sample adoption rate times 100 (as in Innes & Sam 2008). The marginal effects for the probit and the KS models are calculated at the mean of the variables.

Table 5: Marginal effects of selected factors on fertiliser adoption

Pooled model	**Probit model**	**KS model**
Distance to trading Centre (km)	-0.2456	-0.1761
No. of extension visits	8.2192	5.5895
Age of head of household (years)	-1.4642	-1.1298
Average education of household (years)	1.8175	1.2472
Non-farm income (US$)	0.1169	0.7894
Gender of farmer (1 = Male, 0 = Female)	70.3660	49.3191
Male farmer	**Probit model**	**KS model**
Distance to trading centre (km)	-0.1444	-0.1012
No. of extension visits	8.6890	7.1966
Age of head of household (years)	-2.0431	-1.2457
Average education of household (years)	0.1034	-0.5768
Non-farm income (US$)	0.1156	0.0866
Female farmer	**Probit model**	**KS model**
Distance to trading centre (km)	-0.8329	-0.6742
No. of extension visits	1.4303	1.7436
Age of head of household (years)	0.8704	1.5041
Average education of household (years)	7.3400	6.4308
Non-farm income (US$)	0.1313	0.1048

Note: The percentage marginal effect represents the estimated effect of selected factors on fertiliser adoption, as a percentage of the sample average rate of fertiliser adoption.

6. Conclusions and policy implications

We examined the effect of gender on fertiliser adoption in Uganda using a national survey of 1 912 households. We focused on fertiliser use because, although it has significant potential for yield increases, it is poorly adopted. While a number of studies have analysed the fertilizer adoption behaviour of farmers in many developing countries, empirical work on the determinants of fertiliser adoption in Uganda is scarce. We found that male-headed households were more likely to adopt fertiliser than female-headed households. We delved further into the effect of gender on adoption by estimating separate models for male- and female-headed households to determine if the drivers of adoption differ between the households. With respect to male-headed households we found the number of extension visits, the age of the head of household and non-farm earnings to be significant, but education and distance to market insignificant. Conversely, with respect to female-headed households, we found education and distance to market to be significant, but the number of extension visits, age of the head of household and non-farm earnings were insignificant. For both male- and female-headed households we found farm size and household size insignificant. Our results are robust in that they hold using a probit model and a semiparametric single index model.

These findings suggest that different policy instruments will be needed to increase fertiliser adoption by female- versus male-headed households. Policies that increase the number of extension visits and non-farm earnings will have the most pronounced effect on increasing fertiliser adoption among male-headed households. Conversely, policies that reduce transportation costs and subsidise education will have the most pronounced effect on increasing fertiliser adoption by female-headed household. The government and development partners in the agriculture sector can improve the literacy and numeracy skills of women by integrating female adult literacy in the agricultural interventions. In addition, policy interventions that facilitate rural input distribution can reduce the transportation costs incurred to procure inputs from the distinct towns. In the same line, certification of small bags of fertiliser for sale by rural input dealers also may increase the input use by female-headed households.

Although extension and non-farm income were not significant in the model for female-headed households, we argue that policy interventions that facilitate inclusive access to extension services and participation in the non-farm income sector can increase adoption by women. For instance, public extension services and private service providers can reduce the gender gap in access to extension and advisory services by targeting female social networks – to facilitate inclusive technology dissemination.

References

Abdoulaye T & Sanders JH, 2005. Stages and determinants of fertilizer use in semiarid African agriculture: The Niger experience. Agricultural Economics 32:167–79.

Abrar S, Morrissey O & Rayner T, 2004. Crop-level supply response by agro-climatic region in Ethiopia. Journal of Agricultural Economics 55: 289–311.

Aliber M, 2003. Chronic poverty in South Africa: Incidence, causes and policies. World Development 31: 473–90.

Appleton S, 1996. The gender wage gap in three African countries. Economics Series Working Paper No 1996-07, Department of Economics, Oxford University, Oxford.

Asfaw A & Admassie A, 2004. The role of education on the adoption of chemical fertilizer under different socioeconomic environments in Ethiopia. Agricultural Economics 30: 215–28.

Baltasa G & Doyle P, 2001. Random utility models in marketing research: A survey. Journal of Business Research 51(2): 115–25.

Barrett CB, Reardon T & Webb P, 2001. Nonfarm income diversification and household livelihood strategies in rural Africa: Concepts, dynamics, and policy implications. Food Policy 26:315–31.

Benson T, Lubega P, Bayite-Kasule S, Mogues T & Nyachwo J, 2013. The supply of inorganic fertilizers to smallholder farmers in Uganda. Policy Note No 16 (May), International Food Policy Research Institute, Washington DC & Kampala, Uganda.

Buvinić M & Gupta GR, 1997. Female-headed households and female-maintained families: Are they worth targeting to reduce poverty in developing countries? Economic Development and Cultural Change 45: 259–80.

Carrión-Flores CE, Innes R & Sam AG, 2013. Do voluntary pollution reduction programs (VPRs) spur or deter environmental innovation? Evidence from 33/50. Journal of Environmental Economics and Management 66(3): 444–59.

Chirwa WE, 2005. Fertilizer and hybrid seeds adoption among smallholder maize farmers in Southern Malawi. Development Southern Africa 22: 1–12.

De Janvry A & Sadoulet E, 2001. Income strategies among rural households in Mexico: The role of off-farm activities. World Development 29: 467–80.

Diiro GM & Sam AG, 2015. Agricultural technology adoption and nonfarm earnings in Uganda: A semiparametric analysis. Journal of Developing Areas 49(2): 145–62.

Doss CR & Morris ML, 2001. How does gender affect the adoption of agricultural innovations? The case of improved maize technology in Ghana. Agricultural Economics 25: 27–39.

Druilhe Z & Barreiro-Hurle J, 2012. Fertilizer subsidies in sub-Saharan Africa. ESA Working Paper No. 12-04, Food and Agricultural Organization, Rome, Italy.

Duflo E, Kremer M & J. Robinson, 2008. How high are rates of return to fertilizer? Evidence from field experiments in Kenya. American Economic Review 98: 482–8.

Duflo E, Kremer M & Robinson J, 2011. Nudging farmers to use fertilizer: theory and experimental evidence from Kenya. American Economic Review 101: 2350–90.

Ergun AT, Ker AP & Sam AG, 2011. Semiparametric estimation of the link function in binary choice single-index models. Working Paper No. 11-02, Department of Food, Agricultural and Resource Economics, University of Guelph, Guelph, Ontario.

Gordon A, 2000. Improving smallholder access to purchased inputs in Sub-Saharan Africa. Natural Resources Institute, University of Greenwich, Greenwich, UK.

Government of Uganda, 2009. The state of Uganda population report 2009. Addressing the effects of climate change on migration patterns and women. Kampala: Government of Uganda.

Gruhn P & Rashid S, 2001. Problems and constraints in the multiplication of seed and planting materials in Uganda. In P. Jagger & J. Pender (ed.), Policies for improved land management in Uganda. EPTD Workshop Summary Paper No. 10, Washington DC.

Hagos HG, 2012. Tenure (in)security and agricultural investment of smallholder farmers in Mozambique. Working Paper Number 5, International Food Policy Research Institute, Washington DC.

Hanemann WM, 1984. Discrete/continuous models of consumer demand. Econometrica 52: 541–61.

Hausman JA & Wise DA, 1978. A conditional probit model for qualitative choice: Discrete decisions recognizing interdependence and heterogeneous preferences. Econometrica 46: 403–26.

Henao J & Banaante C, 2006. Agricultural production and soil nutrient mining in Africa: Implications for resource conservation and policy development. Muscle Shoals, Alabama, USA: IFDC – An International Center for Soil Fertility and Agricultural Development.

Horowitz JL & Hardle W, 1996. Direct semiparametric estimation of single-index models with discrete covariates. Journal of the American Statistical Association 91: 1632–40.

Ichimura H, 1993. Semiparametric least squares (SLS) and weighted estimation of single-index models. Journal of Econometrics 58: 71–120.

Iiyama M, Kariuki P, Kristjanson P, Kaitibie S & Maitima J, 2008. Livelihood diversification strategies, incomes and soil management strategies: A case study from Kerio Valley, Kenya. Journal of International Development 20: 380–97.

Innes R & Sam AG, 2008. Voluntary pollution reductions and the enforcement of environmental law: An empirical study of the 33/50 program. Journal of Law and Economics 51(2): 271–96.

Isham J, 2002. The effect of social capital on fertilizer adoption: Evidence from rural Tanzania. Journal of African Economies 11: 39–60.

Kelly V, 2006. Factors affecting demand for fertilizer in Sub-Saharan Africa. Agriculture and Rural Development Discussion Paper No. 23, World Bank, Washington DC.

Kilic T, Palacios-Lopez A & Goldstein M, 2013. Caught in a productivity trap: A distributional perspective on gender differences in Malawian agriculture. World Bank Policy Research working paper No. 6381, World Bank, Washington DC.

Klein RW & Spady RH, 1993. An efficient semiparametric estimator for binary response models. Econometrica 61: 387–421.

Larson BA & Frisvold GB, 1996. Fertilizers to support agricultural development in Sub-Saharan Africa: What is needed and why. Food Policy 21:509–25.

Morris M, Kelly V, Kopicki R & Byerlee D, 2007. Fertilizer use in African agriculture: Lessons learned and good practice guidelines. Working Paper No. 39037, World Bank, Washington DC, USA.

Ndiritu SW, Kassie M & Shiferaw B, 2011. Adoption of agricultural technologies in Kenya: How does gender matter? Paper presented at the 28th International Conference of Agricultural Economists, 18–24 August, Rafain Convention Center, Foz Do Iguacu, Brazil.

Nkonya E, Pender J, Kaizzi C, Kato E & Mugarura S, 2005. Policy options for increasing crop productivity and reducing soil nutrient depletion and poverty in Uganda. IFPRI EPT Discussion Paper No. 134, International Food Policy Research Institute, Washington DC, USA.

Okoboi G & Barungi M, 2012. Constraints to fertilizer use in Uganda: Insights from Uganda census of agriculture 2008/9. Journal of Sustainable Agriculture 5: 99–113.

Reardon T, Kelly V, Yanggen D & Crawford E, 1999. Determinants of fertilizer adoption by African farmers: Policy analysis framework, illustrative evidence, and implications. Staff Paper No. 99-18, Department of Agricultural Economics, Michigan State University, East Lansing MI.

Reardon T, Stamoulis K & Pingali P, 2007. Rural nonfarm employment in developing countries in an era of globalization. Agricultural Economics 37: 173–83.

SOFA (The State of Food and Agriculture), 2011. Women in agriculture: Closing the gender gap for development. Available at http://www.fao.org/docrep/013/i2050e/i2050e.pdf

Soule MJ, Tegene A & Wiebe KD, 2000. Land tenure and the adoption of conservation practices. American Journal of Agricultural Economics 82(4): 993–1005.

Suri T, 2011. Selection and comparative advantage in technology adoption. Econometrica 79:159–209.

Uganda Bureau of Statistics, 2010. Abridged report. Government report, UBOS. Kampala, Uganda: Statistics House.

World Bank, 2013. Development indicators database. Washington DC: World Bank.

World Bank, 2014. Gender gap holds back Africa's women farmers: New report identifies policy interventions to narrow and eliminate gender inequality. Available at http://www.worldbank.org/en/news/press-release/2014/03/18/gender-gap-holds-back-africas-women-farmers-new-report-identifies-policy-interventions-to-narrow-and-eliminate-gender-inequality

Yamano T & Arai A, 2010. Fertilizer policies, price, and application in East Africa. GRIPS Discussion Paper No. 10-24, GRIPS, Japan.

Yesuf M & Bluffstone R, 2007. Risk aversion in low income countries: Experimental evidence from Ethiopia. Discussion Paper No. 00715, International Food Policy Research Institute, Washington DC.