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Variety awareness, nutrition knowledge and adoption of nutritionally enhanced crop varieties: Evidence from Kenya

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Abstract

This paper evaluates the impact of variety awareness and nutrition knowledge on the adoption of biofortified crop varieties using a sample of 661 households from Kisii and Nyamira counties in Kenya. The study employs the average treatment effect (ATE) framework to control for information on the KK15 bean variety and knowledge of its nutritional attributes among small-scale farmers. The results show that farmers who had knowledge of the nutritional attributes of KK15 beans were more likely to adopt relative to those who were only aware of the variety. A nutrition attribute knowledge gap of 8% was estimated, which represents the potential adoption loss due to a lack of knowledge of the nutritional benefits. Adoption of biofortified crops can therefore be improved by disseminating information on the varieties and their nutritional attributes. This can be achieved by entrenching nutrition information in extension packages disseminated to farmers.

Key words: biofortification; adoption; nutrition knowledge; variety awareness; nutrition

1. Introduction

Close to a billion people globally are undernourished (FAO *et al*. 2018). A majority of them are small-scale farmers in the rural areas of developing countries and derive their livelihoods from agriculture. The number of undernourished people has stagnated over the last decade, and even increased recently in sub-Saharan Africa (FAO *et al*. 2018). Estimates by the FAO *et al*. (2018) indicate that more than 20% of the population of Kenya is undernourished. Women and children are the most vulnerable to malnutrition because of their high nutritional requirements for growth and development, and their different physiological requirements (Blössner *et al*. 2005). About 26% of Kenyan children are stunted, while 4% are wasted and 11% are underweight (Kenya National Bureau of Statistics [KNBS], 2014).

Micronutrient malnutrition and undernutrition are the main risk factors for child mortality and other health complications in developing countries (International Food Policy Research Institute [IFPRI] 2017; Jäckering *et al*. 2018). The negative impacts of undernutrition are estimated to cost developing countries 2.5% to 10% of their gross domestic product (GDP) (Horton & Ross 2003; Stein & Qaim 2007; IFPRI 2017). According to FAO *et al*. (2019), undernutrition trends are exacerbated by slowing economic growth, conflict, population displacements and climate change, which are prevalent in developing countries. These factors negatively affect agricultural productivity, which in turn weakens food systems and rural livelihoods. The current trends of undernutrition threaten the achievement of the second and third sustainable development goals, which focus on improving nutrition, promoting sustainable agriculture and subsequently achieving good health and wellbeing for people by 2030.

The role of agriculture in reducing the burden of undernutrition has been recognised in the literature (Honfo *et al*. 2010; Masset *et al*. 2012; Fanzo *et al*. 2013). One of the more promising interventions is biofortification. Biofortification is the process of increasing the micronutrient density of a crop through plant breeding, agronomic practices, or transgenic procedures (Pfeiffer & McClafferty 2007). It is relatively cost effective and sustainable, and targets staples that constitute a large proportion of diets consumed regularly by poor households (Nestel *et al*. 2006; Pfeiffer & McClafferty 2007). Empirical evidence from Vitamin A biofortification of orange-fleshed sweet potatoes (OFSP) shows that targeted agricultural programmes for biofortified food crops have a positive nutritional effect (Van Jaarsveld *et al*. 2005). Similarly, research on quality protein maize (QPM) has shown that measurable health impacts can be achieved by increased intakes of balanced protein by substituting common maize with QPM in food intakes (Nuss *et al*. 2011).

One of the challenges affecting the effectiveness of biofortification is achieving the broad adoption and consumption of biofortified crops in target areas (Gilligan 2012). The role of socioeconomic factors in the adoption of new technologies has been studied extensively (Adesina & Baidu-Forson 1995; Foster & Rosenzweig 2010). Besides socioeconomic factors, access to propagation materials for the new crop varieties and knowledge on how to successfully use the technology would influence adoption (Kabunga *et al*. 2012). Beyond those factors, the adoption of new innovations is influenced by awareness of the innovations and information diffusion in the population (Diagne & Demont 2007).

For biofortified varieties, knowledge of the nutritional benefits, in addition to awareness of varieties, could potentially influence adoption and consumption. De Groote *et al*. (2016) find that QPM farmers showed high familiarity with the varieties, but low understanding of their nutritional attributes and benefits – an indication of failure to disseminate information on the nutritional benefits. Accordingly, De Groote *et al*. (2016) found that adopters ranked agronomic performance as more important than nutritional benefits for adoption. Thus, farmers who are aware of the variety but lack knowledge of its nutritional attributes may not adopt biofortified crops. However, the extent to which knowledge of the nutritional benefits and awareness of varieties affects the adoption of biofortified varieties has not been quantified. While this gap has been acknowledged in previous research on the adoption of biofortified crops, it has hardly been addressed in any empirical study. This study evaluates the effect of variety awareness and nutrition knowledge the on adoption of biofortified crop varieties in the Kisii and Nyamira counties of Kenya. The study hypothesised that, in addition to awareness, adoption of biofortified crop varieties is influenced by knowledge of their nutritional attributes.

The study focuses on the adoption of KK15 beans, a new variety that contains high levels of zinc and iron, and thus is important in the fight against micronutrient deficiency in Kenya. The variety faced low dissemination after its release, before Africa Harvest, a local non-governmental organisation (NGO), undertook activities to promote it in 2016.

2. Study methods

2.1 Data sources

This study used survey data collected in 2016 from a sample of 661 smallholder farmers who were members of common interest groups (CIGs). A two-stage sampling procedure was employed to select the farmers. With the assistance of Africa Harvest, a list of all existing CIGs in the area was compiled and a simple, random sampling procedure with a probability proportional to the total number of existing groups was used in the first stage to select 48 groups (32 in Kisii and 16 in Nyamira). In the second stage, a simple random sampling technique was also used to select 20 households from each of the sampled CIGs. The selected households were interviewed in the local languages using semi-structured questionnaires. In cases where some groups had fewer than 20 households, all group members were interviewed.

2.2 Measurement of variables

2.2.1 Dependent variables

The dependent variables in this study are variety awareness, nutrition knowledge and adoption. Recall and self-reporting are the most commonly used methods for measuring awareness and knowledge. Recall data collected through self-reports does not suffer from major bias, even after lengthy periods (Beegle *et al*. 2012). Some inaccuracies that result from a long recall period can be eliminated by applying the 'know by name' method, in which researchers prompt by reading the names of the techniques to farmers when collecting data, as opposed to relying solely on the memory of the respondents (Kondylis *et al*. 2015).

This study used self-reported data on awareness of variety and knowledge of nutritional benefits, as opposed to relying on membership of groups that had participated in promotion activities, or had had contact with the programme. This is because not all members of selected groups attended sessions, and the fact that information and knowledge would have diffused beyond the selected groups. The accuracy of the data was improved through name prompting. In the first question, respondents were asked whether they knew about the KK15 bean variety. The answer was binary and is denoted by r in this study ($r = 1$ if 'yes' and $r = 0$ if 'no').

Only the farmers who answered in the affirmative to the first question were asked the second question, which sought to know whether the respondent had knowledge of the unique nutritional attributes of the variety, in this case its richness in iron and zinc. The answer to the follow-up question was also binary, denoted by k ($k = 1$ if 'yes' and $k = 0$ if 'no'). To reduce the bias caused by false reporting, the answer to the nutrition knowledge question was only entered as affirmative if the respondent could mention the specific nutritional attributes. Kondylis *et al*. (2015) find that jargon can affect farmers' reporting of knowledge even when they are familiar with a practice or attribute. Iron and zinc do not have direct local translations in Kenya, and some farmers could not pronounce them in English. Such farmers reported on the effects of consumption on their health, which are increasing blood levels for iron and boosting immunity for zinc. To obtain data on adoption rates, farmers were asked the quantity in kilograms that they had planted in the previous season.

2.2.2 Measurement of other key variables

The exogenous variables in this study included social networks, distance to produce markets, farm diversity, wealth, access to extension, education, gender of household head, and age of the household head. Following Jäckering *et al*. (2018), a social network index was constructed by counting the number of other persons the farmer interacts with on topics related to food and agriculture within the CIG. Jäckering *et al*. (2018) find that such informal social networks are an important channel for the flow of agriculture and nutrition information in rural Kenya. The distance in kilometres to the produce markets was also considered.

Farm diversity is measured as a count of the species of crops that the farmer already has on the farm, following Sibhatu *et al*. (2015). The current level of farm diversification may affect farmers' decisions on whether or not to add an extra crop variety on the farm. Access to extension services was measured by the number of times the farmer interacted with extension officers. Land size was also expected to influence adoption positively, as farmers with smaller portions may have exhausted farm space, unless they displace other crops. A Likert scale, ranging from better to worse to no difference was used to measure the farmers' perceptions of the performance of KK15 beans on pre-listed attributes compared to his/her preferred local variety.

2.3 Analytical framework

The study applied the average treatment effect (ATE) framework to evaluate the effect of awareness of the variety and nutrition knowledge on adoption. ATE estimation is commonly used in evaluating programmes such as job training and medical treatment (Wooldridge 2010). The method is suitable when the explanatory variable of interest is binary. Other methods that can be used when the explained variable is binary include probit and logit models. However, these models are prone to exposure and selection biases. Non-exposure bias results in an underestimation of the population adoption rate, as farmers not exposed to a new technology cannot adopt it (Diagne & Demont 2007; Kabunga *et al*. 2012; Dontsop Nguezet *et al*. 2013). Similarly, selection bias results from adoption by farmers who are exposed first, or 'progressive' farmers who most likely interact with technology promoters, leading to overestimation of the population adoption rate.

This study was potentially subject to exposure and selection biases, as it focuses on the role of information diffusion in relation to the biofortified varieties and their nutritional benefits on adoption. Diagne and Demont (2007) show that the observed adoption rates as calculated from sample computation and classical adoption models such as logit and probit are not accurate when exposure to the technology is not complete in the population. The ATE framework is therefore appropriate for this study, as it models actual adoption while controlling for non-random selection.

According to Wooldridge (2010), the quantity of interest (ATE) is defined as the expected effect of 'treatment' on an individual selected randomly from the population. The ATE framework has some weakness in policy research. This is because, in defining the average result for the entire population, the individuals who did not participate or were not even eligible are included (Heckman 1997). However, this weakness can be eliminated by excluding those who are not eligible for certain programmes from the analysis (Wooldridge 2010).

Following Wooldridge (2010), the potential mean adoption outcome (ATE) of the population, conditional on covariates *x*, is presented in equation (1).

$$ATE = E(y_1 - y_0|x), \tag{1}$$

where y_1 is the potential adoption outcome of a farmer when exposed to the intervention, and y_0 is the potential adoption outcome of a farmer when not exposed to the intervention

The average treatment effect when the farmer is aware of the variety (variety awareness unconstrained) is expressed in equation (2):

$$ATE'T_r = E(y_1 - y_0|x, r = 1) \tag{2}$$

The average treatment effect when the farmer is both aware of the variety and knowledgeable on the nutritional attributes of the variety (variety awareness and nutrition knowledge unconstrained) is expressed as:

$$ATE'T_{rk} = E(y_1 - y_0|x, r = 1, k = 1) \tag{3}$$

The third outcome of interest is what Dontsop Nguezet *et al*. (2013) define as the average treatment effect on the untreated (ATE'U), which is expressed as:

$$ATE'U_{rk} = E(y_1 - y_0 | x, r = 0, k = 0) \quad (4)$$

The three outcomes of interest are consistent and unbiased when estimated using the ATE framework, subject to a condition that the distribution of r and k (exposure) are independent of y_0 and y_1 (potential outcome), and conditional on a vector of covariates x (Wooldridge 2002; Dontsop Nguezet *et al*. 2013).

2.4 Estimation strategy

In this study, the two-stage estimation approach of Kabunga *et al*. (2012) is adopted, in which two levels of information exposure are accounted for, that is awareness of the technology and knowledge of the nutritional benefits. In the first stage, the model estimates the probability of adoption and the adoption rates of KK15 beans among farmers who are aware of the variety. The study estimated parameters for a binary adoption variable (yes = 1, no = 0), and also for the quantity of seed grown in the previous season in kilograms. In the second stage, two models were estimated to analyse the determinants of adoption after controlling for awareness of the variety and knowledge of its nutritional attributes. The first model used data for all farmers who were aware of the variety, while the second analysed data only for those who had knowledge of the nutritional attributes of the variety. The estimations were carried out using STATA 13 statistical software, with the user-written add-on command '*adoption*', developed by Diagne and Demont (2007).

3. Results

3.1 Descriptive statistics

Table 1 presents descriptive results of the household socioeconomic characteristics disaggregated by adoption status. A *t*-test of the difference of means was carried out to determine differences in the characteristics between the two categories.

Table 1: Descriptive results for household socio-economic characteristics by adoption status

Variables	Means			t-test
	Adopters (N = 137)	Non-adopters (N = 534)	Total sample (N = 661)	
Proportion of male farmers (%)	73.7	74.7	74.5	0.24
Age of HH head (years)[1]	53	49.8	50.5	-2.68***
Education of HH head (years)	9.1	8.9	8.9	-0.58
Age of female spouse (years)[1]	48	44.6	45.3	-2.81***
Education of female spouse (years)[1]	7.7	8.3	8.1	1.76*
Size of land owned (acres)	1.6	1.4	1.5	-1.17
Number of extension visits [1]	6.2	2.6	3.3	-9.86***
Household size	5.5	5.4	5.5	-0.38
Distance to village market (km)	2	1.9	1.9	-0.53
Distance to agricultural produce market (km)	3.9	4.5	4.4	1.46
Distance to tarmac road (km)	3	3.4	3.3	0.81
Farm diversity (crop count)[1]	12.4	11.1	11.3	-4.06***
On-farm income (1 000 Kshs)[1]	68.7	10.6	76.5	-2.72***
Off-farm income (1 000 Kshs)	132.9	116.6	120	-1.11

[1] Notes: ***, ** and * show that the mean values for KK15 adopters are significantly different from those of non-adopters at the 1%, 5% and 10% levels respectively. Exchange rate US $1 = Kshs 103.

The *t*-test results reveal that there were no significant differences between adopters and non-adopters with regard to gender of household head, even though the majority of the farmers were male (75%). The average age of adopters was significantly higher than that of non-adopters. Nutrition requirements change as individuals advance in age, thus adoption is expected to vary with age if the new varieties are adopted for nutrition. The observed differences between levels of education of the household heads of adopters and non-adopters were not significant. The mean education years of adopters was slightly higher than that of non-adopters. However, differences in the education levels of female spouses between adopters and non-adopters were significant.

The study does observe significant differences between adopters and non-adopters in the size of land owned. On average, adopters had more interaction with agricultural agents relative to non-adopters, which implies that, as expected, interaction with extension agents is associated with decision to adopt improved varieties.

Perception of KK15 beans

Table 2 presents results for the farmers' perceptions of KK15 beans regarding selected attributes. The number of farmers are reported for each category and the percent of farmers is shown in parentheses.

Table 2: Farmers' perceptions of KK15 bean variety attributes

Characteristic	Adoption status	Better	Worse	No difference	Don't know	Pearson chi^2
Maturity period	Total	(347) 86)	3 (1)	14 (3)	37 (9)	18.7 ***
	Adopters [1]	128 (96)	1 (1)	3 (2)	1 (1)	
	Non-adopters	217 (82)	2 (1)	11 (4)	36 (13)	
Yield	Total	334 (82)	13 (3)	13 (3)	43 (10)	15.3 ***
	Adopters [1]	122 (91)	4 (3)	5 (4)	3 (2)	
	Non-adopters	212 (79)	8 (3)	7 (3)	40 (15)	
Pest and disease resistance	Total	211 (52)	28 (7)	74 (18)	90 (22)	33.9 ***
	Adopters [1]	90 (67)	12 (9)	24 (18)	8 (6)	
	Non-adopters	120 (45)	16 (6)	49 (18)	82 (31)	
Marketability	Total	118 (29)	96 (23)	32 (7)	157 (38)	18.1 ***
	Adopters [1]	46 (34)	44 (33)	9 (7)	35 (26)	
	Non-adopters	71 (27)	51 (19)	23 (9)	122 (46)	
Taste	Total	238 (59)	12 (3)	17 (4)	136 (34)	79.7 ***
	Adopters [1]	120 (90)	2 (1)	4 (3)	8 (6)	
	Non-adopters	117 (44)	10 (4)	13 (5)	127 (48)	

[1] Note: ***, ** and * show perceptions of KK15 bean variety adopters are significantly different from those of non-adopters at the 1%, 5% and 10% levels respectively.

A majority of farmers perceived KK15 beans as being similar or superior to other varieties in the attributes that were considered. This was so for both adopters and non-adopters (Table 2). As such, farmers' adoption decisions could not have been affected substantially by perceived inferior attributes of the variety. It therefore was expected that nutrition knowledge would result in increased adoption rates, as reported in previous studies (Hotz *et al*. 2012; De Groote *et al*. 2016).

3.2. Econometric results and discussion

3.2.1 Adoption rates of KK15 bean variety

The parametric estimates of the ATE model are presented in Table 3. The results, based on the binary adoption variable, are interpreted as percentages.

Table 3: ATE parametric estimation of population adoption rates

	Linear models		Probit models	
	Variety awareness unconstrained	**Nutrition knowledge unconstrained**	**Variety awareness unconstrained**	**Nutrition knowledge unconstrained**
ATE [1]	0.626*** (0.101)	0.882*** (0.122)	0.297*** (0.021)	0.381*** (0.025)
ATE1 [1]	0.731*** (0.101)	0.949*** (0.134)	0.325*** (0.021)	0.389*** (0.025)
ATE0 [1]	0.441*** (0.119)	0.597*** (0.128)	0.246*** (0.026)	0.346*** (0.029)
JEA [1]	0.465*** (0.065)	0.772*** (0.109)	0.208*** (0.014)	0.318*** (0.020)
GAP [1]	-0.162*** (0.043)	-0.110*** (0.024)	-0.089*** (0.010)	-0.063*** (0.005)
PSB [1]	0.104*** (0.030)	0.066*** (0.025)	0.028*** (0.007)	0.008*** (0.003)
Observed				
Exposure rate			0.638*** (0.019)	0.818*** (0.019)
Adoption rate			0.207*** (0.016)	0.317*** (0.023)
Adoption rate among exposed [1]	0.727*** (0.108)	0.945*** (0.145)	0.325*** (0.025)	0.387*** (0.028)
Number of observations	640	398	661	407
Number of exposed	407	324	442	333
Number of adopters	130	125	137	129

[1] Notes: *** and ** denote statistical significance at the 1% and 5% levels respectively. Robust standard errors reported in parentheses.

Sixty-four percent of the respondents we aware of the KK15 variety. Of those aware, 82% had knowledge of the nutritional benefits of the variety. The observed adoption rate was 21% among those aware of the variety, and 32% among those who had knowledge of the nutritional attributes. The joint exposure and adoption (JEA) rate corresponds to the actual adoption rate, at 21%. However, the JEA and observed adoption rates are not accurate indicators of adoption due to non-exposure bias (Diagne & Demont 2007). The true population adoption rate corresponds to the ATE, which is the predicted adoption rate after adjusting for heterogeneous information exposure.

The ATE when awareness of the variety was not a constraint was 30%, and 38% when knowledge of the nutritional attributes was not a constraint. This shows an estimated adoption gap of 8%, which can be interpreted as the nutrition attribute knowledge gap. The ATE as measured by the quantity of seed grown was 0.6 kg for the awareness unconstrained group and 0.9 kg for the nutrition knowledge unconstrained group. Thus, the average demand for KK15 bean seeds would have been 0.6 kg if all farmers were aware of the variety and 0.9 kg if all farmers were aware of the variety and knew the nutritional benefits.

The estimated adoption rate among the variety awareness unconstrained subpopulation ($ATE'T_r$) and the variety awareness and nutrition knowledge unconstrained subpopulation ($ATE'T_k$) was 33% and 38% respectively. When measured by the amount of seed grown, the estimated *ATE'Tr* and *ATE'Tk* were 0.73 and 0.95 respectively. The *ATE'Tr* was less than *ATE'Tk* by only five percentage points. The *ATE'T* was consistently higher than ATE, indicating a positive and statistically significant population selection bias (PSB) for the variety aware group as well as the nutrition knowledge group. The PSB for variety aware was 2.8%, and it was 0.8% for the farmers with knowledge of the nutritional benefits of KK15. The potential adoption rate among farmers who had not been exposed to the variety and who did have nutritional knowledge of the variety was 25% and 35% respectively. The KK15 variety awareness exposure gap was 9%, while the nutrition knowledge gap was 6%.

3.2.2 Determinants of KK15 adoption

Tables 4 and 5 present the regression results for the determinants of the adoption of the KK15 bean variety based on model specifications for parametric linear regression results estimated for the quantity of seed. Model 1 presents the results for respondents who were aware of the variety, while the results for respondents who possessed knowledge of the nutritional attributes are presented in model 2. The results of classical probit and ordinary least squares (OLS) are presented alongside the ATE results for comparison. The practical difference between ATE and classic regression is that ATE uses the exposed sub-sample (awareness of variety or knowledge of nutritional attributes), while the classic model uses the full sample (Dontsop Nguezet *et al*. 2013).

Table 4: Parametric linear regression results for determinants of KK15 adoption

	(1) Variety awareness		**(2) Nutrition knowledge**	
	1 (a) Classic	**1 (b) ATE**	**2 (a) Classic**	**2 (b) ATE**
Variables	**Coefficient**	**Coefficient**	**Coefficient**	**Coefficient**
Social network index [1]	0.014* (0.007)	0.022** (0.011)	0.021* (0.011)	0.026* (0.013)
Distance to produce market [1]	-0.021** (0.011)	-0.041** (0.018)	-0.049** (0.021)	-0.055** (0.024)
Wealth index [1]	0.120* (0.062)	0.204** (0.101)	0.175* (0.105)	0.204 (0.125)
Gender of HH head	0.015 (0.128)	0.058 (0.188)	0.024 (0.196)	-0.057 (0.243)
Size of land owned (acres)	-0.044 (0.070)	-0.077 (0.096)	0.124 (0.200)	0.142 (0.225)
Age of HH head (years)[1]	-0.140 (0.087)	-0.238* (0.136)	-0.263* (0.139)	-0.342* (0.181)
Farm diversity (crop count)	0.018 (0.015)	0.032 (0.023)	0.023 (0.027)	0.044 (0.033)
Ease of acquiring credit (dummy)[1]	0.182** (0.091)	0.330** (0.159)	0.369** (0.177)	0.481** (0.226)
Number of extension visits [1]	0.115*** (0.023)	0.094*** (0.027)	0.126** (0.052)	0.120** (0.057)
Education of HH head	-0.001 (0.013)	-0.001 (0.022)	0.004 (0.025)	0.007 (0.030)
Household size	-0.010 (0.026)	0.002 (0.043)	0.029 (0.057)	-0.033 (0.070)
Number of observations	627	401	392	318
F(9, 618) Prob > F	7.47 0.00	7.91 0.00	6.86 0.00	7.05 0.00

[1] Notes: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively. Robust standard errors are reported in parentheses.

Table 5 similarly presents four model specifications for parametric probit regression results using the binary adoption variable as dependent variable.

Differences in significance and direction of influence are observed between the results of the classic and ATE models. For the purpose of this study, therefore, only the ATE results are interpreted.

The quantity of seeds grown by a farmer increased with the size of social network a farmer had. Although the direction is positive, social networks do not appear to significantly affect the probability of adoption (model 3). In keeping with the *a priori* expectations, interaction with extension agents and access to credit increased the likelihood of a farmer adopting KK15 beans. The wealth index was significant at 1% for the quantity of KK15 bean seeds grown for the variety-aware unconstrained group, but not for the nutrition knowledge unconstrained group. The wealth index was significant at 5% for the probability of adoption (models 3 and 4).

Table 5: Parametric probit regression results for determinants of KK15 adoption

	(3) Variety awareness		(4) Nutrition knowledge	
	3 (a) Classic	**3 (b) ATE**	**4 (a) Classic**	**4 (b) ATE**
Variables	**Coefficient**	**Coefficient**	**Coefficient**	**Coefficient**
Social network index	0.002 (0.006)	0.004 (0.007)	0.003 (0.007)	0.004 (0.008)
Distance to produce market [1]	-0.036** (0.017)	-0.042** (0.018)	-0.033* (0.018)	-0.031* (0.018)
Wealth index [1]	0.084* (0.045)	0.122** (0.051)	0.137*** (0.053)	0.140** (0.057)
Gender of HH head (dummy)	-0.029 (0.148)	0.138 (0.168)	0.147 (0.173)	0.152 (0.184)
Size of land owned (acres)[1]	-0.057 (0.049)	-0.093* (0.048)	-0.096* (0.049)	-0.095* (0.051)
Age of HH head (years)[1]	-0.344*** (0.079)	-0.315*** (0.085)	-0.355*** (0.091)	-0.357*** (0.103)
Farm diversity (crop count)[1]	0.051*** (0.018)	0.060*** (0.020)	0.059*** (0.020)	0.086*** (0.023)
Ease of acquiring credit (dummy)	-0.011 (0.173)	0.005 (0.195)	0.109 (0.207)	0.112 (0.226)
Number of extension visits [1]	0.121*** (0.022)	0.079*** (0.020)	0.085*** (0.022)	0.070*** (0.023)
Education of HH head [1]	-0.043** (0.017)	-0.044** (0.020)	-0.048** (0.020)	-0.053** (0.022)
Household size	-0.032 (0.031)	-0.016 (0.035)	-0.019 (0.036)	-0.029 (0.039)
Number of observations	645	415	400	326
Wald chi^2 (11)	258.3	85.35	86.37	48.11
Prob > chi^2	0.00	0.00	0.00	0.00
Log likelihood	-286.13	-238.61	-225.59	-196.80

[1] Notes: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively. Robust standard errors are reported in parentheses.

Distance to produce market and age of the household head negatively affected the probability of adoption and quantity of KK15 beans seeds grown, while farm diversity had a positive and significant effect on the probability of adoption. The farmers who already grew diverse crops probably did so for nutrition and food sufficiency purposes, and therefore were willing to adopt more crops for a similar purpose.

The quantity of KK15 beans grown increased with the farmers' perceptions of ease of acquiring credit. Farmers who perceived that they could easily acquire credit adopted more relative to those who perceived credit services as difficult to access. This is expected, as the farmers who perceived access to credit as easy are either wealthy and creditworthy, or willing to take a risk. Previous studies have found an association between access to credit and adoption of new varieties (Zeller *et al*. 1998; Matuschke *et al*. 2007).

4. Discussion

The findings of this study show that not all farmers were aware of the KK15 bean variety. In addition, not all farmers who were aware of the variety had knowledge of the nutritional attributes of the variety. The implication of this incomplete information diffusion is confirmed by the positive PSB for variety awareness and nutrition attribute knowledge. Thus, the adoption rate among the targeted subpopulation was likely to overestimate the true adoption rate in the population. This finding agrees with results from studies by Diagne and Demont (2007), Kabunga *et al*. (2012) and Dontsop Nguezet *et al*. (2013) on the implications of selection bias and exposure bias for adoption estimation.

Because the PSB is positive and statistically significant for variety awareness, the null hypothesis – that the KK15 variety-aware subpopulation was equally likely to adopt as the general population – is rejected. The implication is that the probability of adoption by a farmer selected from the variety-aware subpopulation was different than for a farmer randomly selected from the general population. The null hypothesis – that the subpopulation with nutrition knowledge of the KK15 variety was equally likely to adopt the variety as the general population – is also rejected. Because the PSB is positive and significant, the study concludes that a farmer selected from the subpopulation of farmers who had knowledge of the nutrition benefits of KK15 had a higher probability of adopting than a farmer randomly picked from the general population. This confirms the positive effect of nutrition information on the adoption of biofortified crops, and agrees with the findings of previous studies (Chowdhury *et al*. 2010; Hotz *et al*. 2012; De Groote *et al*. 2016).

The ATE estimation shows a positive adoption gap between those who were aware of the variety and those with knowledge of its nutritional benefits. This nutrition attribute knowledge gap represents a potential adoption loss of 8% due to the lack of knowledge of the nutritional benefits. Thus, adoption would have increased by 8% if all farmers were aware of the nutritional attributes of the variety. Thus, there is potential for increasing the adoption of KK15 beans by increasing awareness of it and knowledge of its nutritional benefits.

Regarding the factors that influence adoption, our findings agree with the results of some previous studies. Social networks influence adoption rates for farmers, an indication of information flow on the new varieties among farmers. Jäckering *et al*. (2018) find that social networks are important channels for the flow of information on agriculture and nutrition.

Farmers who had increased interaction with extension agents were more likely to adopt the variety. Numerous studies have previously shown the positive role of extension services in the adoption of new varieties (Feleke & Zegeye 2006; Dontsop Nguezet *et al*. 2013; Elias *et al*. 2013). This finding indicates that extension agents could be an important channel of passing nutrition information on biofortified crops to farmers.

Similar to the findings of Shikuku *et al*. (2014), it was found that, relative to older farmers, younger farmers were more likely to adopt KK15 beans. Younger farmers are more likely to be of child-bearing age. Kaguongo *et al*. (2010) found that the presence of children younger than five years of age in the households increased the intensity of adoption of orange-fleshed sweet potatoes in Kenya. These farmers would similarly find it more beneficial to adopt the bean variety for nutritional purposes.

Contrary to *a priori* expectations, education of the household head negatively affected the probability of adoption of the KK15 bean variety. This is not totally implausible. It could be that more educated farmers are aware of alternative sources of nutrition that they are able to acquire from the market. They therefore are not likely to grow a new variety whose target is only nutritional. In addition, more educated farmers are more likely to be engaged in off-farm employment and therefore not readily available to access the information through the available information channels for the specific technology.

Access to markets also influences adoption. The market is an important source of planting material, is a market for the produced commodities, and a source of information on new varieties. Farmers who are located in remote areas, far away from markets, could lack both access to and information on the new varieties. Previous studies have shown the importance of access to planting materials for adoption to occur (Kabunga *et al*. 2012). Distance to market is also a proxy for transaction costs, which reduce adoption.

5. Conclusions

The ATE framework is applied in this study to control for the incomplete diffusion of information on KK15 beans and knowledge of its nutritional attributes in the population. The results show that, among farmers who were aware of the variety, a majority perceived KK15 beans as better than other varieties in the attributes that were considered. This finding suggests that non-adoption that may result from any perceived inferior quality of the variety relative to other varieties was substantially eliminated.

The study also finds that not all farmers that were aware of the variety had knowledge of its nutritional attributes. Farmers who had knowledge of the nutritional attributes of KK15 beans were more likely to adopt it relative to farmers who were only aware of the variety. This indicates the positive impact of nutrition knowledge on the adoption of biofortified crop varieties, relative to basic awareness of the varieties. Other factors that were found to influence adoption included access to markets, education level and age of the household head.

6. Policy implications

The findings of this paper suggest that there is a need to increase the dissemination of information on the nutritional benefits of biofortified crops so as to achieve broad adoption. One way of achieving this is through development organisations and government agencies that are involved in promoting these varieties. They should embed the information on nutritional benefits in packages disseminated to farmers when promoting the adoption of biofortified crops.

Farmers interact regularly with extension service providers. The focus of these services has mainly been agronomy. The dissemination of nutrition information should be given the same level of prominence as agronomy information. Efforts to improve nutrition can benefit when the ministry responsible for agriculture and that for health collaborate in developing policies aimed at making extension services more 'nutrition sensitive'. In addition, there is a need for the government to reskill extension officers on 'nutrition extension' so as to equip them with the skills necessary to train farmers on the nutritional benefits of the various varieties.

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