The effect of climate change adaptation strategies on bean yield in central and northern Uganda

Benard Onzima*
Department of Agribusiness and Natural Resource Economics, Makerere University, Kampala, Uganda. E-mail: benardonzima@yahoo.com

Enid Katungi
International Centre for Tropical Agriculture (CIAT), Kampala, Uganda. E-mail: e.katungi@cgiar.org

Jackline Bonabana-Wabbi
Department of Agribusiness and Natural Resource Economics, Makerere University, Kampala, Uganda. E-mail: jbexim@gmail.com

* Corresponding author

Abstract

This paper analyses the impact of adaptation to climate change on bean productivity on a micro-scale using instrumental variable techniques in a two-stage econometric model, using data collected from farming households in northern and central Uganda. We employed the bivariate probit technique to model simultaneous and interdependent adoption decisions, and the ordered probit to model the intensity of adaptation. We modelled the impact of adaptation using instrumental variables and the control function approach because of the potential endogeneity of the adaptation decision. The driving forces behind adoption of the two selected adaptation strategies were heterogeneous. Location-specific factors influenced the intensity of adaptation between the two study regions. The effect of adaptation was stronger for households that used a higher number of strategies, evidence that the two adaptation strategies need to be used simultaneously by farmers to maximise the positive impact of adaptation.

Key words: adaptation; beans; instrumental variables; endogeneity; Uganda

1. Introduction

In recent decades, changes in climate have manifested in increased incidences of extreme weather, and climate events have emerged as among the most serious global challenges (IPCC 2014). Current evidence suggests that temperatures in Africa are projected to rise faster than the global average increase during the 21st century (Niang *et al*. 2014). In Uganda, changes in temperature could reach a 1.5°C to 2°C annual average increase by 2030 (Caffrey *et al*. 2013), higher than the temperature increase observed over the past six decades. Higher temperatures mediate faster loss of soil moisture, create favourable conditions for some pests and diseases to multiply, and lead to the loss of arable lands (Hisali *et al*. 2011). Crop simulation studies have predicted that climate change will have an overall negative effect on the yields of major crops across Africa (Thornton *et al*. 2009; Niang *et al*. 2014; Ramirez-Villegas & Thornton 2015).

Common beans are generally sensitive to high temperatures because of their mid- to high-altitude origin, and the crop is constrained by biotic and abiotic stresses existing in the different environments where it is grown (Beebe *et al*. 2013). Simulation studies show that common bean will suffer a decline in productivity under variable temperature and precipitation conditions (Caffrey *et al*. 2013; CIAT 2015). Rising temperatures will also reduce the area suitable for bean production by 30% to 50% in eastern Africa in the 21st century if adaptation does not occur (Ramirez-Villegas & Thornton 2015). This will severely reduce the availability of beans for consumption and could worsen the problems of hidden hunger, especially among people with limited access to animal-based food. In Uganda, the crop is planted on about 669 000 hectares of land annually (FAOSTAT 2016) and contributes an equivalent of 24% of the total daily per capita protein intake (Soniia *et al*. 2001; Larochelle *et al*. 2017). It is ranked among the top five foods with the highest micronutrient-to-price concentration ratio (Drewnowski 2010) and provides income to millions of smallholder producers, thus addressing the challenges of poverty and malnutrition. Due to rapid population growth and urbanisation, there is pressure to intensify bean production in sub-Saharan Africa. It therefore is crucial that the crop is effectively adapted to long-term changes in climatic conditions.

Following the National Adaptation Programme of Action on climate change for Uganda, climate change adaptation refers to "adjustments in practices, processes, or structures to take into account changing climate conditions, to moderate potential damages, or to benefit from opportunities associated with climate change (NAPA 2007). For bean crops, adaptation to climatic variations has been an integral component of bean improvement research since its domestication. African agricultural research organisations and their international collaborators, especially the International Center for Tropical Agriculture (CIAT), have developed many varieties, some of which are tolerant to biotic or abiotic constraints (such as drought and heat, excessive rainfall and disease) and thus climate smart (PABRA 2018). In Uganda, the National Agricultural Research Organisation (NARO) has released 32 varieties since 1968, two of which (NABE2 and NAROBEAN1) are drought tolerant and recommended for drought-prone areas. Recent strategies aim to enhance farmers' access to weather-smart information for supporting decision-making on which varieties to plant, as well as to adjust their cropping calendar. Previous experimental studies have confirmed the suitability of some of the adaptation strategies recommended for common bean in increasing yields (Hailu *et al*. 2015).

While bean adaptation to climate change has been ongoing at the national and international levels, little research has been conducted to shed light on farm-level adaptation of the bean crop to climate change and its effect on crop productivity. Such information would add valuable information for the design of policies for common bean resilience enhancement, as it would provide evidence on the drivers and barriers of bean adaptation to climate change. Some studies have identified the determinants of farm-level adaptation of agriculture to long-term climate change risks (Nhemachena & Hassan 2007; Di Falco *et al*. 2011; Teklewold *et al*. 2013). Other researchers have demonstrated the effect of agricultural adaptation practices on food productivity in Ethiopia (Di Falco *et al*. 2011) and food security in Pakistan (Ali & Erenstein 2017). However, as pointed out by Mendelsohn (2012) and Thornton *et al*. (2010), the pattern of adaptation is likely to vary greatly over space and time, or by crop – requiring context-specific research to pinpoint efficient strategies and options.

This paper estimates the micro-level effect of adaptation strategies on common bean productivity in Uganda using econometric modelling techniques. To the best of our knowledge, we know of no such study that has been done for bean in Uganda. A few studies done in Uganda have focused on understanding farmers' perceptions of climate risk, coping strategies and the impact of climate change on coffee and maize (Jassogne *et al*. 2013; Kikoyo & Nobert 2016; Mubiru *et al*. 2015). Other studies that have evaluated the effect of common bean adaptation strategies on yield elsewhere did so under researcher-managed experiments that do not fully represent farmers' conditions (Hailu *et al*. 2015).

The next section describes the sources of data and its collection procedures, while the analytical framework used for modelling adaptation is described in Section 3. Section 4 presents the results of the study, while the main conclusions are presented in Section 5.

2. Survey design, data collection and adaptation strategies

2.1 Survey design and data collection

The study was conducted in two regions of Uganda where bean production is susceptible to drought: the central and northern regions. From these regions, nine districts were selected purposively for the study, because these fall in the drought corridor and thus are vulnerable to climate change. Although both agro-ecological zones experience a bimodal type of rainfall that falls from March to June and July to November and support a wide diversity of annual and perennial crops, they experience a lot of variation in rainfall. Annual rainfall ranges from 800 to 1 400 mm. Beans are grown in both cropping seasons. A stratified sampling method was followed in selecting primary sampling units (PSUs) and households from PSUs in each region. A total of four substrata were created by dividing the sub-counties in the targeted districts into four groups, based on rainfall received and distance to the main tarmac road (dry – good market access, dry – poor market access, wet – good market access and wet – poor market access). In each substratum, three sub-counties were randomly selected for data collection, and two parishes were selected from each subcounty. One village was randomly selected from each parish, and 10 households (478 in total) were randomly selected for the study from each village.

2.2 Understanding adaptation strategies available to bean growers

In order to understand the strategies available to bean growers, we consulted with communities' representatives and sought their views on climatic variations in their communities. In the majority of the villages, participants indicated having experienced a decrease in rainfall duration, a change in onset dates and a decrease in cumulative rainfall amounts. Communities in both regions have also observed some effects of the climatic variations on beans in the form of wilting, which they attribute to drought and high temperatures. Available strategies to cope with the consequences of these climatic conditions, as reported by the participants, included: 1) intercropping beans with other crops, 2) early planting, 3) applying pesticides, 4) planting fast-maturing varieties, 5) adjusting planting dates, 6) applying organic/green manure, 7) planting drought-tolerant bean varieties, 8) earthing-up to enhance soil fertility, 9) inorganic fertiliser, 10) mixing varieties on the same plot, 11) planting beans in swampy areas and 12) planting beans under shade trees.

The identified strategies were rated for effectiveness in addressing the identified hazards. Following Huang *et al*. (2015), we excluded practices rated as ineffective from further analysis. Out of the adaptation strategies rated as effective, only two categories, viz. genetic resources (drought-tolerant and early-maturing varieties) and weather-smart practices (early planting and adjusting planting calendar) had sufficient observations at the household level to ensure validity of the statistical results. Thus, they form the components of the technological package for the adaptation of beans to climate change in the analysis of this paper. These strategies have been recommended by the NARO.

Sampled households were classified as adapters and non-adapters, depending on their adoption of the two selected strategies (varietal adaptation and adjusting the farming calendar). On this basis, 74% of the households were classified as adapters. However, slightly over half of the households used just a single adaptation strategy (Table 1).

Table 1: Classification of households by adaptation status

Region	Adaptation (1 adapter; 0 non-adapter) - % hhs	Varietal adaptation (1 drought-tolerant/fast-maturing variety; 0 otherwise) - % hhs	Adjusting the farming calendar (1 yes; 0 no) - % hhs	% of households using one adaptation strategy	% of households using two adaptation strategies	Average number of strategies used by adapters
Central	52	32	29	42	9	1.18
North	92	84	37	62	30	1.32
Total	74	61	33	53	20	1.28

Source: Survey data

3. Analytical framework and estimation technique

The yield outcomes of adaptation to climate change by bean farmers can be conceptualised as a two-step sequential process (Di Falco *et al*. 2011; Asfaw *et al*. 2013; Huang *et al*. 2015). In the first step, a farmer is hypothesised to adapt to climate variability by implementing one or several strategies simultaneously in response to long-term changes in mean temperature and rainfall. Then the effect of this adaptation on yield outcome is observed in the second step. The general equation for bean production can be specified as:

$$\boldsymbol{Q_i} = \boldsymbol{\alpha X_i} + \boldsymbol{\beta D_i} + \boldsymbol{\varepsilon_i}\,, \qquad (1)$$

where $\boldsymbol{Q_i}$ is the output of beans per hectare for household i, $\boldsymbol{D_i}$ is decision to adapt to climate change measured as the number of strategies used, and $\boldsymbol{X_i}$ is a vector representing factors that typically influence bean yield in smallholder farming systems. These factors can broadly be categorised into three: inputs, farm-level and household/individual characteristics, and climatic variables. $\boldsymbol{\varepsilon_i}$ is the normal stochastic error term reflecting unobserved characteristics that also affect bean yield.

The impact of adaptation to climate change on bean yield could easily be determined by estimating the ordinary least squares (OLS) regression of bean yield on the explanatory variables described in yield equation (1), with adaptation decision included directly as an explanatory variable. This approach, however, introduces a bias that may skew the estimates (Di Falco *et al*. 2011; Ogutu *et al*. 2014; Huang *et al*. 2015) when the adaptation decision is endogenous – which violates the assumption of exogeneity for the validity of the OLS model.

3.1 Correcting for endogeneity

The instrumental variable (IV) regression technique that assumes a joint normal error distribution is the solution to explicitly account for such endogeneity (Di Falco *et al*. 2011). To correct for possible endogeneity of adaptation in yield outcome, we use a control function approach (CFA). This approach allows to test and control for the potential endogeneity of an explanatory variable in the outcome function (Smith & Blundell 1986; Imbens & Wooldridge 2008; Lewbel *et al*. 2012). The CFA assumes that the adoption of climate change adaptation strategies, our endogenous variable, can be expressed as a function of all exogenous variables entering the yield equation, denoted by X_i (in equation (1)), plus at least one IV estimated in the first stage. The generalised residuals from the first-stage estimation of adaptation using the ordered probit model (in equation (3)) were predicted and then included as an additional regressor in the reduced yield function (equation (4)). This two-stage procedure provides unbiased and consistent estimates of the effect of adoption of climate change adaptation strategies on yield if at least one variable in the selection model can be effectively excluded from the yield equation (Ogutu *et al*. 2014).

A valid IV should influence the decision to adapt to climate change in the first stage (equation (3)), without itself being determined by any confounding factors affecting the yield outcome. In this case, the variable chosen as an instrument must be correlated with the adoption of climate adaptation strategies, but not with the error term of the yield models (Asfaw *et al*. 2013). The choice of a valid instrument thus depends on intuition, economic reasoning and its statistical properties. In selecting instrumental variables, we follow recent studies (Di Falco *et al*. 2011; Asfaw *et al*. 2013) and use market access (measured at community level as a dummy capturing household proximity to a tarmac road) and the coefficient of variation of precipitation in the two years prior to the survey. Being located closer to good roads is expected to result in enhanced access to technologies and information, but we do not expect any direct influence on yield. Similarly, weather conditions experienced prior to planting will influence production decisions, but will have no direct effect on yield outcomes of the production decisions in the current period. The exogeneity of the IVs was supported by their lack of individual and joint statistical significance in the yield model for non-adapters based on a falsification test (the result of the falsification test is available upon request).

3.2 Empirical estimation

3.2.1 First stage – ordered probit estimation of adaptation intensity

In the first stage, the decision to adapt to climate change, defined as the number of strategies to apply, was estimated. Although adaptation is conceptually a sequential process that involves the formation of perceptions by the farmer after accessing information, and then decision-making on whether or not to adapt, we combined the stages in this process for simplicity. The decision to adapt a strategy is modelled in a random utility framework following Asfaw *et al*. (2013) and Khonje *et al*. (2015). The difference between the utility from adaptation (U_{Ai}) and non-adaptation (U_{Ni}) of these measures by farmer i may be denoted as Y^*. A utility-maximising farm household will choose to adapt, if the utility gained from adapting is greater than the utility of not adapting at all ($Y^* = U_{Ai} - U_{Ni} > 0$).

Farmers are assumed to choose the bundle that maximises utility. We used an ordered probit in the first stage to measure the intensity of adaptation (measured by the number of adaptation strategies adopted by a farmer), but a bivariate probit, as shown in Green (2002), to draw more insights on factors that may determine the use of each individual strategy. For brevity, we omit the econometric specification of the bivariate probit, but this can be made available upon request. An ordered probit is the appropriate specification in the first stage, since the dependent variable is ordered, ranging from zero for non-adapters to two for full adapters. Since the adoption of several climate adaptation strategies is a latent variable determined by several explanatory variables, the ordered probit is specified following Wooldridge (2012):

$$\boldsymbol{y_i}^* = \boldsymbol{\beta X_i} + \boldsymbol{\varepsilon_i}, \qquad \boldsymbol{i = 1, 2, 3, \ldots, N}, \tag{2}$$

where E $(\varepsilon_i|x_i) = 0$ and Var $(\varepsilon_i|x_i) = 1$.

Treating y_i, the observed variable, as a categorical variable with j response categories and as a proxy for the latent random variable y_i^*, and $\mu_{-1},\ \mu_0,\ \mu_1 \ldots\ \mu_{J-1}, \mu_j$ as a vector of unobservable cutpoints, the relationship between the observed and the latent variables can be written as:

$$y_i = j \quad if\ \mu_{j-1} < y_i^* \leq \mu_j, \quad j = 0, 1, 2, \ldots, J, \text{ where } \mu_{-1} = -\infty,\ \mu_0 = 0,\ \mu_j = \infty$$

As y_i^* is unobserved, what we observe is:

$$\begin{aligned} y_i &= 0 \; if \; y_i^* \leq 0 \\ &= 1 \; if \; 0 < y_i^* \leq \mu_1 \\ &= 2 \; if \; \mu_1 < y_i^* \leq \mu_2 \end{aligned}$$

μ_1 and μ_2 are unobserved parameters to be estimated with the parameters β. The empirical model of this study is specified as:

$$\boldsymbol{y_{ij}} = \boldsymbol{\alpha X_i} + \boldsymbol{\beta Z_i} + \boldsymbol{\varepsilon_i}, \tag{3}$$

where y is adaptation intensity proxied by the number of strategies used by household i, j (j = 0, 1, 2) represents the three alternative dependent dummy variables indicating whether a household (i) did not use any adaptation strategy, (ii) used only one strategy or (iii) used both strategies considered in this study. The vector X is a set of exogenous explanatory variables, and Z represents the instrumental variables discussed in sub-section 3.1 as influencing the adaptation intensity but not the yield outcomes. We derive the generalised residuals from the first-stage ordered probit model using the formula in Cameron and Trivedi (2005).

3.2.2 Second-stage estimation of effect of adaptation on yield

Using the CFP approach, adaptation dummy variables and generalised residuals are added in equation (3):

$$\boldsymbol{Q_i} = \boldsymbol{\alpha X_i} + \boldsymbol{\beta D_i} + \boldsymbol{\varphi \bar{\omega}_i} + \boldsymbol{\mu_i} \tag{4}$$

Q, X, β remain as defined in equation (1). The generated residuals ($\bar{\omega}_i$) are derived from the first-stage estimation of the ordered probit (equation (3)) to test and control for endogeneity of the adaptation in equation (4), if present. Vector $\boldsymbol{X_i}$ includes inputs used in bean production (i.e. labour, organic fertilisers (manure and compost), chemical fertilisers and pesticides and shifters of the yield function). Also, added to the model are dummy variables for the number of adaptation strategies (D_i), which takes a value of 0 to 2. Vector μ_i consists of variables that influence yield but were unobserved to the researcher, whereby $E(\mu_i) = 0$ and cov $(\mu_i, \varepsilon_i) = 0$.

4. Empirical results and discussion

4.1 Descriptive results

A comparison of the yield between adapters and non-adapters reveals that non-adapters realised higher yields than adapters at the 5% level of significance (Table 2). Further disaggregation of the data by region revealed that both adapters and non-adapters in the central region obtained significantly higher yields than their counterparts in the northern region, at the 1% and 5% levels of significance respectively. This is because climatic conditions are relatively more severe in the northern region than in the central region – thus average yield difference between adapters and non-adapters observed is skewed by region-specific factors. Other plot-level differences between adapters and non-adapters are elaborated in Table 2.

Table 2: Descriptive characteristics of sampled bean production plots by adaptation status

	Non-adapters (n = 151)		Adapters (n = 420)		Total (n = 571)	
Variables	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**
Yield by adaptation status (kg/ha)						
Yield	333.20	355.15	254.58	315.41	275.37	327.91
Yield by region (kg/ha)						
Central	364.70	377.02				
North	181.78	151.54				
Central			394.56	448.98		
North			189.71	198.43		
Yield by number of strategies used (kg/ha)						
One adaptation strategy			241.86	253.20		
Two adaptation strategies			287.51	436.95		
Inputs used						
Labour (man days per hectare)	252.86	315.87	201.34	235.22	214.84	259.48
Seed rate (kg/ha)	83.42	88.79	74.45	71.90	76.82	76.73
Fertiliser (1 yes; 0 otherwise)	0.05	0.22	0.01	0.12	0.02	0.15
Manure (1 yes; 0 otherwise)	0.05	0.21	0.01	0.11	0.02	0.14
Pesticide (1 yes; 0 otherwise)	0.25	0.44	0.21	0.41	0.22	0.42
Ranking of rainfall by subcounty						
Dry subcounty (1 yes; 0 otherwise)	0.36	0.48	0.18	0.38	0.23	0.42
Average subcounty (1 yes; 0 otherwise)	0.03	0.18	0.09	0.29	0.08	0.27
Wet subcounty (1 yes; 0 otherwise)	0.60	0.49	0.73	0.45	0.70	0.46
Plot physical characteristics						
Sandy loam (1/0)	0.48	0.50	0.66	0.48	0.61	0.49
Sandy clay loam (1/0)	0.29	0.46	0.18	0.38	0.21	0.41
Black clay (1/0)	0.06	0.24	0.04	0.20	0.05	0.21
Other soil type (1/0)	0.17	0.37	0.12	0.33	0.13	0.34
Crop stand (1 pure stand; 0 otherwise)	0.46	0.50	0.48	0.50	0.48	0.50

Source: Survey data, 2016

4.2 Econometric results

4.2.1 Determinants of adaptation to climate change among bean growers

The diagnostic test of goodness of fit performed using Wald statistics has a chi-square (χ^2 (22)) value of 238.49 ($p < 0.01$), confirming that the variables included in the ordered probit model jointly explain variations in the adaptation intensity. The same variables also jointly explain the probability that a household will select a specific adaptation strategy ($\chi^2 = 240.57$, $p < 0.01$). The likelihood ratio test that there is no covariance between the error terms across the two equations was rejected ($\chi^2(1) = 7.39$, p < 0.01), which supports the hypothesis that the decision to use the two strategies is not mutually exclusive. Thus, a bivariate probit was an appropriate specification for the data. The results reveal a weak substitution effect with a negative sign (-0.27), implying that farmers tend to use one strategy at a time rather than both, yet a combination would generate a higher yield, as suggested in stage two.

An F-test for the joint significance of the two IVs: coefficient of variance (CoV) of precipitation in 2014 and 2015 and distance to tarmac road indicate that the IVs are strong predictors of adaptation intensity.[1] Both IVs were individually significant at p < 0.01 in the adaptation intensity equation estimated in the first stage. As expected, the CoV of precipitation in 2014 was positively correlated with the number of strategies combined. Conversely, the CoV of precipitation in 2015 had a negative and significant association with varietal adaptation, adjusting the farming calendar and the intensity

[1] The F-test has a value ($\chi^2(22) = 238.49$, $p = 0.00$), as shown in model (2) in Table 3.

of adaptation. The reasons for this are unclear, although this could potentially be associated with the short timespan between 2015 and 2016 to implement any meaningful adaptation measures.

Table 3: Determinants of adaptation estimated with bivariate probit and ordered probit models

	Model 1: Bivariate probit regression				Model 2: Ordered probit regression	
Variables	Varietal adaptation		Adjusting the farming calendar			
	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
Sex of household head (1 male; 0 otherwise)	-0.38*	0.21	0.04	0.16	-0.07	0.15
Log of age of household head (years)	0.08	0.22	0.32*	0.18	0.24	0.17
Education level of head (years)	0.01	0.02	-0.02	0.02	-0.01	0.02
Tools and implements (score)	0.02**	0.01	0.01	0.01	0.02***	0.01
Producer association membership (1 yes; 0 otherwise)	0.66	0.40	-0.45	0.40	0.11	0.33
Access to extension (1 yes; 0 otherwise)	-0.06	0.23	-0.08	0.20	-0.22	0.18
Weather information (1 yes; 0 otherwise)	0.29	0.40	0.35	0.32	0.59**	0.30
Distance to tarmac road (1 = < 10 km; 0 otherwise)	0.38**	0.16	0.21	0.13	0.33***	0.12
Log of labour (man days/ha)					-0.01	0.07
Log of seed rate (kg/ha)					-0.10	0.07
Rainfall (base: dry)						
Average (1/0)	-0.75**	0.37	0.19	0.30	-0.37	0.28
Wet (1/0)	-0.34	0.22	0.28	0.21	0.01	0.19
Manure (1 yes; 0 otherwise)					-0.72*	0.40
Fertiliser (1 yes; 0 otherwise)					-1.05***	0.40
Pesticides (1 yes; 0 otherwise)					-0.45***	0.15
Crop stand (1 pure stand; 0 otherwise)	-0.24	0.15	0.13	0.12	-0.05	0.11
Soil type (base: sandy loam)						
Sandy clay loam (1/0)	0.36*	0.21	-0.16	0.17	0.04	0.15
Black clay (1/0)	1.02***	0.37	0.11	0.29	0.62**	0.27
Other soil type (1/0)	0.39*	0.24	0.34*	0.18	0.50***	0.17
CoV of precipitation 2014 (mm)	8.01***	1.41	2.05*	1.14	6.27***	1.08
CoV of precipitation 2015 (mm)	-9.28***	1.91	-2.96*	1.54	-7.11***	1.46
Region (1 north, 0 otherwise)	2.69***	0.25	0.12	0.19	1.66***	0.19
Constant	-0.36	1.13	-1.58*	0.95		
/cut1					-0.04	0.93
/cut2					2.03	0.94
/athrho	-0.27***	0.10				
Rho	-0.27*	0.09				
Log likelihood	-511.37				-396.95	
Number of obs.	520				513	
Wald $chi^2(34)$/LR $chi^2(22)$	240.57				238.49	
Prob > chi^2	0.00				0.00	
Pseudo R^2					0.23	

Source: Survey data, 2016

Wald test of rho = 0: $chi^2(1) = 7.3892$; Prob > $chi^2 = 0.0066$. Number of observations refers to the number of bean plots. Asterisks *, ** and *** denote significance at the $p < 0.10$, $p < 0.05$ and $p < 0.01$ levels respectively

Short distance to tarmac road, used as a proxy for market access, was positively associated with the intensity of adaptation ($p < 0.01$) and uptake of varietal adaptation ($p < 0.05$). This result confirms the expectation that being located closer to a good road network may encourage the adoption of new technologies, as it eases mobility, facilitates inflow of information from sources external to the community, and reduces transaction costs. This is consistent with the findings from research by Teklewold *et al*. (2013) on the adoption of sustainable agricultural practices in rural Ethiopia.

Age of the household head does not seem to matter in adaptation intensity, but was found to be positively and significantly correlated with adjusting the farming calendar. This suggests that older household heads with better farming experience and knowledge of historical climate trends have a higher propensity to adjust their farming calendars. Nhemachena and Hassan (2007) obtained similar results in southern Africa.

Household wealth, measured by the score (value) of tools and implements owned, was positively and significantly associated with the intensity of adaptation, as well as with the use of a varietal adaptation strategy, consistent with the results report by Teklewold *et al*. (2013) from Ethiopia and Nhemachena and Hassan (2007) from Southern Africa. Greater endowments of farm tools and implements can facilitate timely farming operations – thus enabling farmers to adjust their farming management practices and technologies. As expected, access to weather forecast information was positively and significantly associated with the intensity of adaptation. Similar results were reported by Di Falco *et al*. (2011) in Ethiopia, where farmers who were informed about the weather were more likely to adopt strategies to cope with expected changes.

Inputs such as manure, fertiliser and pesticides were negatively and significantly associated with the intensity of adaptation, perhaps because these inputs indirectly mitigate yield loss. For instance, the usage of manure enhances soil moisture retention, while fertiliser and pesticides enhance plant vigour, thus minimising the absolute negative consequences of rainfall failure on household welfare.

Finally, the results also show that there are location-specific factors that are captured by the regional dummy to explain variations in the intensity of adaptation between the two regions. On average, the number of adaption strategies were 1.7 points higher in the northern region than in the central region (significant at $p < 0.01$). The bivariate model also revealed that households in the northern region were more likely to undertake varietal adaptation compared to their counterparts in central Uganda ($p < 0.01$) because of the greater severity of climate hazards of drought and heat stress in the northern region (Thornton *et al*. 2009; Beebe *et al*. 2011; Ramirez-Villegas & Thornton 2015).

4.2.2 Effect of adaptation on yield

The results from the second stage of estimation are presented in Table 4. The coefficient of the generalised residuals included to test for the endogeneity of adaptation in the yield function was not significant, which suggests that the adaptation decisions towards these strategies could be exogenous in the yield function. However, we maintained them in the equation to show the results of this test. The Wald test confirms the importance of variables included in explaining variations in bean yields ($F(21, 491) = 9.32$, *p value* = 0.00).

The results indicate that the number of adaptation strategies used had a strong and significant effect on yield. Farmers who adopted a single climate change adaptation strategy realised significantly higher yields than farmers who did not adopt a single strategy ($p < 0.10$), while the effect of adaptation was stronger for households that used both strategies ($p < 0.01$). More specifically, farmers who adopted a single strategy harvested 38% more per hectare than non-adapters, and those who adopted two strategies harvested double (103%) the amount harvested by non-adapters on the same unit of land (Table 5). This is evidence that the two selected adaptation strategies need to be used simultaneously by farmers to maximise the positive impact of adaptation. Other studies have also found that the adoption of adaptation or risk-mitigating strategies increases food productivity (Di Falco *et al*. 2011; Asfaw *et al*. 2013; Huang *et al*. 2015).

Table 4: Effect of adaptation on yield

	Yield function	
	Coefficient	Standard error
Sex of household head (1 male; 0 otherwise)	-0.08	0.10
Log of age of household head (years)	-0.33***	0.11
Education level of head (years)	0.02	0.01
Tools and implements (score)	0.01	0.00
Log of labour (man days/ha)	0.14***	0.05
Log of seed rate (kg/ha)	0.31***	0.05
Manure (1 yes; 0 otherwise)	0.19	0.25
Fertiliser (1 yes; 0 otherwise)	-0.26	0.24
Pesticides (1 yes; 0 otherwise)	0.22*	0.13
Rainfall		
Average rainfall subcounty (1/0)	0.28	0.19
Wet subcounty (1/0)	0.33***	0.12
Crop stand (1 pure stand; 0 otherwise)	0.00	0.08
Soil type (base: sandy loam)		
Sandy clay loam (1/0)	-0.18*	0.10
Black clay (1/0)	-0.08	0.18
Other soil type (1/0)	-0.08	0.12
Producer association membership (1 yes; 0 otherwise)	0.40*	0.21
Access to extension (1 yes; 0 otherwise)	0.29***	0.10
Region (1 north, 0 otherwise)	-0.95***	0.18
Adaptation with one strategy	0.32*	0.19
Adaptation with two strategies	0.71***	0.26
Residuals of ordered probit model	-0.56	0.34
Constant	4.19***	0.52
Number of observations	513	
F (21, 491)	9.32	
Prob > F	0.00	
R-squared	0.29	
Adjusted R-squared	0.25	
Root MSE	0.81	

Source: Survey data
Number of observations refers to the number of bean plots. Asterisks *, ** and *** denote significance at the $p < 0.10$, $p < 0.05$ and $p < 0.01$ levels respectively

Access to extension and membership of producer associations were found to positively influence bean yield, perhaps through information. Farmers who received advice from extension workers in 2015 harvested 34% more beans per hectare compared to those who did not. Similarly, members of producer associations harvested 49% more per hectare compared to farmers who did not belong to producer associations. The higher yields realised by farmers who received extension advice and those who associated with producer associations are a result of better information on production decisions. Farmers with extension contacts have better chances of being aware of changing climatic conditions and the management practices they can use to adapt to these changes (Nhemachena & Hassan 2007).

The results also reveal that farmers in the northern region, where drought is more severe, realised yields that are 61% lower than those obtained by their counterparts in central Uganda. This is consistent with the simulation studies of Thornton *et al*. (2009), who predicted that, without adaptation, there would be a reduction in bean production in the mixed rain-fed humid and sub-humid zones of Uganda, such as northern Uganda, by 2050.

5. Conclusions

The findings of this study indicate that market conditions and access to weather information exert a positive influence on the likelihood of adaptation to climate change by bean growers. Information is accessed through different sources, but farmers who have an association with rural farmer associations seem to be a critical source of information for farmers in Uganda. The role of these farmer associations has proven more pivotal in an environment in which public extension services have largely broken down. This suggests that interventions by public services can play an important role in facilitating adaptation and increasing adaptive capacity. This is particularly important for poorer households who are unable to access such services on their own, as is evident from the strong and positive association of the wealth indicators (i.e. ownership of tools and implements) with the uptake of adaptation measures.

This study also found that location-specific factors, captured by controlling for the region, explain variations in the choice of adaptation strategies used between the two regions. Our research shows that the drought hazard is more severe in northern Uganda compared to central Uganda. This influences the choice of varietal adaptation as the preferred strategy in northern Uganda, implying that the degree of climate risk is important and ought to be factored in when disseminating adaptation strategies. Where risk is high, the benefits of adaption are likely to be high as well, and the pull forces will facilitate adaptation.

This study confirms that varietal adaptation and adjusting the farming calendar are effective in addressing the drought hazard in the study areas and significantly increasing the yield of beans. These strategies seems to complement each other, as farmers who used both strategies realised much higher yields than those who used only one of the strategies. However, we note that the proportion of farmers using these strategies is limited, possibly as a consequence of limited information on the best suited strategies or combination of strategies to adapt to the drought hazard. The importance of location in the choice of adaptation strategies implies that there possibly are several other strategies in other bean-growing areas that may have a positive effect on yield. There thus is need for more research in other bean-growing areas to identify the bundle of preferred adaptation strategies in order to build a comprehensive list of strategies that could facilitate the adaptation of bean cultivation to the drought hazard.

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References

Ali A & Erenstein O, 2017. Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan. Climate Risk Management 16: 183–94. doi.org/10.1016/j.crm.2016.12.001

Asfaw S, McCarthy N, Lipper L, Arslan A & Cattaneo A, 2013. Adaptation to climate change and food security: Micro-evidence from Malawi. ESA Working Paper, FAO, Rome, Italy.

Beebe S, Ramirez-Villegas J, Jarvis A, Rao IM, Mosquera G, Bueno JM & Blair MW, 2011. Genetic improvement of common beans and the challenges of climate change. In Yadav SS, Redden RJ, Hatfield JL, Lotze-Campen H & Hall AE (eds.), Crop adaptation to climate change. First edition. Oxford UK: John Wiley & Sons.

Beebe S, Rao I, Mukankusi C & Buruchara R, 2013. Improving resource use efficiency and reducing risk of common bean production in Africa, Latin America and the Caribbean. In Hershey C & Neate P (eds.), Eco-efficiency: From vision to reality. Cali, Colombia: CIAT.

Caffrey P, Finan T, Trzaska S, Miller D, Laker-Ojok R & Huston S, 2013. Uganda Climate Change Vulnerability Assessment Report. Report to the United States Agency for International Development by Tetra Tech ARD, Washington DC, USA.

Cameron AC & Trivedi PK, 2005. Microeconometrics: Methods and applications. Cambridge UK: Cambridge University Press.

CIAT, 2015. Climate change research. Available at http://ciat.cgiar.org/climate-change-research. (Accessed 5 February 2015).

Di Falco S, Veronesi M & Yesuf M, 2011. Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. American Journal of Agricultural Economics 93(3): 829–46.

Drewnowski A, 2010. The Nutrient Rich Foods Index helps to identify healthy, affordable foods. The American Journal of Clinical Nutrition 91: S1095–101.

FAOSTAT, 2016. Crops. Rome: Food and Agriculture Organization. Available at http://faostat3.fao.org/download/Q/QC/E (Accessed 15 March 2016).

Green WH, 2003. Econometric analysis. Fifth edition. Upper Saddle River NJ: Prentice Hall..

Hailu N, Fininsa C & Tana T, 2015. The effect of climate change resilience strategies on productivity of common beans (*Phaseolus vulgaris*. L) in semi-arid areas of eastern Hararghe, Ethiopia. African Journal of Agriculture Research 10(15): 1852–62. doi:10.5897/AJAR2015.9634

Hisali E, Birungi P & Buyinza F, 2011. Adaptation to climate change in Uganda: Evidence from micro level data. Global Environmental Change 21 (2011): 1245–1261.

Huang J, Wang Y & Wang J, 2015. Farmers' adaptation to extreme weather events through farm management and its impacts on the mean and risk of rice yield in China. American Journal of Agricultural Economics 97(2): 602–17.

Imbens GM & Wooldridge JM, 2008. Recent developments in the econometrics of program evaluation. Journal of Economic Literature 47(1): 5–86.

IPCC, 2014. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Geneva: IPCC.

Jassogne L, Läderach P & Van Asten P, 2013. The impact of climate change on coffee in Uganda. Lessons from a case study in the Rwenzori Mountains. Oxford: Oxfam GB.

Khonje M, Manda J, Alene DA & Kassie M, 2015. Analysis of adoption and impacts of improved maize varieties in eastern Zambia. World Development 66 (2015): 695–706.

Kikoyo DA & Nobert J, 2016. Assessment of impact of climate change and adaptation strategies on maize production in Uganda. Physics and Chemistry of the Earth 93: 37–45.

Larochelle C, Katungi E & Cheng Z, 2017. Pulse consumption and demand by different population subgroups in Uganda and Tanzania. International Centre for Tropical Agriculture, Pan-Africa Bean Research Alliance (PABRA), Kampala, Uganda.

Lewbel A, Dong Y & Yang TT, 2012. Comparing features of convenient estimators for binary choice models with endogenous regressors. Boston College Working Papers in Economics, Boston College Department of Economics, Boston MA, USA.

Mendelsohn R, 2012. The economics of adaptation to climate change in developing countries. Climate Change Economics 3(2): 1250006.

Mubiru DN, Kyazze FB, Radeny M, Zziwa A, Lwasa J & Kinyangi J, 2015. Climatic trends, risk perceptions and coping strategies of smallholder farmers in rural Uganda. CCAFS Working Paper No. 121, CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), Copenhagen, Denmark.

NAPA, 2007. National Adaptation Programme of Action on Climate Change in Uganda. Kampala, Uganda: Ministry of Water and Environment.

Nhemachena C & Hassan R, 2007. Micro-level analysis of farmers' adaptation to climate change in Southern Africa. IFPRI Discussion Paper No. 714, International Food Policy Research Institute, Washington DC, USA.

Niang I, Ruppel OC, Abdrabo MA, Essel A, Lennard C, Padgham J & Urquhart P, 2014. Africa. In Barros VR, Field CB, Dokken DJ, Mastrandrea MD, Mach KJ, Bilir TE, Chatterjee M, Ebi KL, Estrada YO, Genova RC, Girma B, Kissel ES … White LL (eds.), Climate Change 2014: Impacts, adaptation, and vulnerability. Part B: Regional aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press.

Ogutu SO, Okello JJ & Otieno DJ, 2014. Impact of information and communication technology-based market information services on smallholder farm input use and productivity: The case of Kenya. World Development 64: 311–21.

PABRA, 2018. Pan African Bean Research Alliance Database. Available at http://database.pabra-africa.org/?location=breeding&locId=225 (Accessed 6 May 2018).

Ramirez-Villegas J & Thornton PK, 2015. Climate change impacts on African crop production. CCAFS Working Paper No. 119. CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), Copenhagen, Denmark

Smith RJ & Blundell RW, 1986. An exogeneity test for a simultaneous equation tobit model with an application to labor supply. Econometrica 54(3): 679–85.

Soniia D, Kirkby R & Kasozi S, 2001. Assessing the impact of bush bean varieties on poverty reduction in Sub-Saharan Africa: Evidence from Uganda. CIAT, Pan African Bean Research Alliance, Kampala, Uganda.

Teklewold H, Kassie M & Shiferaw B, 2013. Adoption of multiple sustainable agricultural practices in rural Ethiopia. Journal of Agricultural Economics 64: 597–623.

Thornton PK, Jones PG, Alagarswamy G & Andresen J, 2009. Spatial variation of crop yield response to climate change in East Africa. Global Environmental Change 19: 54–65.

Thornton PK, Jones PG, Alagarswamy G, Andresen J & Herrero M, 2010. Adapting to climate change: Agricultural system and household impacts in East Africa. Agricultural Systems 103: 73–82.

Wooldridge JM, 2012. Econometric analysis of cross section and panel data. Cambridge MA & London: The MIT Press.