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Full Length Research Paper

Determinants of adoption of multiple climate change adaptation strategies in Southern Malawi: An ordered probit analysis

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This paper aimed to identify factors affecting adoption of multiple climate change adaptation strategies in Southern Malawi. An ordered probit model was estimated using survey data collected in Nsanje and Balaka districts in 2014-2015 cropping season. Age of household head, total land area owned, petty trading and formal employment were found to reduce the probability of adopting more than two CSA strategies. Farmers who reported observing changes in moisture levels in their areas for the 20-year period prior to the survey were found to have lower probability of adopting four CSA strategies as compared to those who reported not observing any changes in moisture in the same time period. Importantly, being a lead farmer, which proxied ample access to climate smart agriculture extension messages and training access, acreage used in agricultural production and observing an increase in incidences of floods in a 20-year period prior to this study increased the probability of adopting more than two CSA strategies. Interestingly, household income was found not to affect number of CSA strategies adopted. The study recommends that relevant stakeholders should provide farmers with CSA-related extension messages if more farmers are to adopt multiple CSA techniques.

Key words: Climate-smart agriculture, adoption, marginal effects, probability, ordered probit.

INTRODUCTION

Impacts of climate-related shocks on agricultural systems have put building resilient systems to the forefront of agricultural policies globally. Of late, policymakers and development practitioners have increased interest in getting as many farmers as possible to adopt sustainable production practices that strengthen agricultural systems. Among a multiplicity of strategies that are being used to mitigate the agricultural impacts of climate change, the so called Climate Smart Agriculture (CSA) practices that help sustainably increase agricultural productivity; adapt and building resilience of agricultural and food security systems and reduce greenhouse gas emissions from

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agriculture (FAO, 2013) have shown much promise. The interesting work that has now been left for researchers is to inform policymakers on the determinants of adoption of these CSA practices so as to enable them enact practicable strategies that will see farmers adopt the aforementioned practices.

Fortunately, a considerably large number of empirical research has been conducted over the years to understand factors that affect farmer adoption of Climate-Smart Agriculture (Teklewold et al., 2013; Wollni et al., 2010; Nyong et al., 2007). However, a vast majority of the current research has only focused on assessing the determinants of one CSA strategy, albeit CSA is a package of practices that is adopted by farmers in various combinations (Pannell et al., 2014; Teklewold et al., 2013). Indeed, farmers enjoy a variety of benefits by adopting multiple strategies as some of the strategies are complements and substitutes (Teklewold et al., 2013). Therefore, adopting multiple CSA techniques help build a sustainable agricultural production systems well resilient to climate-related and other shocks. Currently, no research has been conducted in Malawi that informs policymakers on determinants of adoption of such a multiplicity of CSA technologies. This paper, therefore, tries to close this information gap by assessing the determinants of smallholder farmer adoption of several CSA strategies using data collected from farmers from Balaka and Nsanje districts in Southern Malawi.

In this paper, the authors have considered smallholder adoption of soil and water conservation, soil fertility improvement, irrigation and water harvesting as well as farm enterprise (portfolio) diversification since they are the main CSA strategies that are practiced in the study area. Following Teklewold et al. (2013), Wollni et al. (2010) as well as D'Souza et al. (1993), we have used the number of these CSA practices that a household practices as a measure for level of adoption of CSA practices which we have fitted as the regressand in an ordered probit model. Greene (2008), Teklewold et al. (2013) and Wollni et al. (2010) noted that as opposed to Poisson models that assume equal probability of adoption for all CSA technologies, in reality, adoption of the second or more technologies are conditioned by adoption of the first technology. This then supports our use of ordered probit as the ordering of the response variable allows us to explicitly incorporate the experience that the farmer has obtained from practicing the first technology.

The model results indicate that the probability of adoption of more than two strategies was negatively affected by age of household head, total land area owned, petty trading and formal employment were found to reduce the probability of adopting more than two CSA strategies. Farmers who reported observing changes in moisture levels in their areas for the 20-year period prior to the survey were found to have lower probability of adopting four CSA strategies as compared to those who reported not observing any changes in moisture in the same time period. Paradoxically, household income was found not to affect number of CSA strategies adopted. Overall, this study contributes to the understanding of factors affecting adoption of subpackages of CSA.

METHODOLOGY

Study description

The study focused on technology adoption as a choice over four practices involving 1) portfolio diversification, 2) soil and water conservation, 3) soil fertility improvement, 4) irrigation/rain water harvesting and our control were farmers in zero or no adaptation category (Table 1).

Sampling and data

Data used in the study were collected in 2014-15 cropping season from households using a semi-structured questionnaire. The study employed multistage sampling whereby Nsanje and Balaka districts in southern Malawi were purposely selected due to their vulnerability to climate related disasters like droughts and floods and the need to find strategies that can make households in the districts more resilient to climate-related shocks. Within a district, traditional authorities were randomly selected. Villages within each traditional authority were then randomly selected. Households that were interviewed were obtained using simple randomly sampling from the selected villages. The sample size was determined following a formula recommended by Krejcie and Morgan (1970) as follows;

$$n = \frac{\chi^2 NP(1-P)}{d^2(N-1)+\chi^2 P(1-P)}$$

Where n is the sample size, χ^2 is tabulated Chi-Square for a one degree of freedom at the desirable confidence level (3.841); N is the population size; P is proportion of adopters (assumed P=0.5 to obtain maximum sample size as the true population P was not known), whereas d is the degree of accuracy presented as a proportion (0.1). Ten percent of the calculated sample size was used to account for possibilities of non-response.

Analytical framework

The decision to adopt climate change adaptation technologies is largely conditioned by farmer's perception of the benefits that will accrue to them once they adopt a technology against perceived costs and risks associated with the technologies (Wollni et al., 2010). Therefore, in adopting climate smart agriculture technologies, the farmer tries to maximize some utility function while minimizing costs in a Marshallian demand framework. There are possibilities, however, that the utility maximizing solution can be one or multiple CSA technologies that a farmer may choose to adopt.

Climate Smart Agriculture is generally a complex system that

Table 1. Definitions of CSA technologies under study.

CSA technology	As defined in this study
Portfolio diversification	Using improved crop varieties, intercropping, different crop varieties that survive in adverse climatic conditions
Soil and water conservation	Farmers' use of mulching, planting of cover crops, minimum tillage operations (conservation agriculture), full tillage operation and digging ridges across slopes
Soil fertility improvement	Agroforestry, applying fertilizer and organic manure
Irrigation/rain water harvesting	Involving storage and supplying water to the farm
No / zero adaptation	Farmers not using any adaptation method to counteract the negative impact of climate variability

involves different technologies and soil management practices (Wollni et al., 2010). Farmers may adopt one or many of these technologies depending on their preference (Teklewold et al., 2013). The main analytical challenge that emanates from adopting multiple technologies in various combinations is connected to defining a cutoff point between adopters and non-adopters. Practically, a majority of farmers just adopt a number of adaption strategies and not others. This then makes it possible for us to handle the aforementioned challenge by using the number of CSA technologies as the dependent variable for our Ordered Probit model, noting the ordinal nature of the response variable (Teklewold et al., 2013; Wollni et al., 2010; Boz and Akbay, 2004). Given that the dependent variable is count in nature, it is normal to think about Poisson regression models. However, as Greene (2008), Teklewold et al. (2013) and Wollni et al. (2010) noted, Poisson models assumed equal probability of adoption for all CSA technologies, whereas in reality, adoption of the second or more technologies are conditioned by adoption of the first technology. This then supports the use of ordered probit as the natural ordering of the response variable allows us to explicitly incorporate the experience that the farmer has obtained from practicing the first technology.

As alluded to the above, the authors have analyzed the model in a random utility framework. The response variable represents the number of CSA technologies that the farmer has adopted. It shows us whether a farmer has adopted zero $(\omega_i = 0)$, one $(\omega_i = 1)$, two $(\omega_i = 2)$, three $(\omega_i = 3)$ or four $(\omega_i = 4)$ various technologies. It is assumed that farmers choose to adopt the number of CSA practices so as to maximize the following underlying utility function:

$$U_i = V_i(\beta x_i) + u_i \text{ for } i = 1, ..., n$$

Where V_i, which is the observed part of the utility function, is a function of a vector of exogenous household, plot and institution-related variables, x_i, and a vector of parameters to be estimated, β, and is assumed to be equivalent to the mean of the random variable U_i (Wollni et al., 2010). Further, it is assumed that the unobserved part of utility function is represented by i.i.d random error term u_i with mean of zero (Greene, 2008). Therefore, the farmer adopts an additional technology if the utility they obtain from adopting it is greater that the utility they obtain if they do not adopt the additional technology (Wollni et al., 2010; Daykin and Moffat, 2002). According to Daykin and Moffat (2002), the utility U_i of each individual farmer is not observed; however, it was observed that:

$$\omega_i = 1 \text{ if } U_i \le \alpha_1$$
$$\omega_i = 2 \text{ if } \alpha_1 \prec U_i \le \alpha_2$$
$$\omega_i = 3 \text{ if } \alpha_2 \prec U_i \le \alpha_3$$
$$\omega_i = 4 \text{ if } \alpha_3 \prec U_i \le \alpha_4$$

Where $\alpha_1 \prec \alpha_2 \prec \alpha_3 \prec \alpha_4$ are "cutoff or threshold" parameters that are estimated using β. Daykin and Moffat (2002) posited that β does not contain intercept term as the term is normalized to zero to allow the threshold parameters to be "free" parameters. Alternatively, Greene (2008) suggested that one of the threshold parameters can simply be normalized.

We have followed Wollni et al. (2010) and Daykin and Moffat (2002) in assuming that u_i is normally distributed such that we can actually get the following probabilities:

$$prob(\omega = 0 \mid x) = \text{prob}(\text{U} \le \alpha_1 \mid \text{x})$$
$$= prob(\beta'\text{x} + \text{u} \le \alpha_1 \mid \text{x}) = \Phi(\alpha_i - \beta'\text{x}),$$
$$prob(\omega = 1 \mid x) = \Phi(\alpha_2 - \beta'\text{x}) - \Phi(\alpha_1 - \beta'\text{x}),$$
$$prob(\omega = 2 \mid x) = \Phi(\alpha_3 - \beta'\text{x}) - \Phi(\alpha_2 - \beta'\text{x}),$$
$$prob(\omega = 3 \mid x) = \Phi(\alpha_4 - \beta'\text{x}) - \Phi(\alpha_3 - \beta'\text{x}),$$
$$prob(\omega = 4 \mid x) = 1 - \Phi(\alpha_4 - \beta'\text{x})$$

Where $\Phi(\bullet)$ is the standard normal cumulative distribution function. The parameters α and β are estimated by the following log-likelihood function:

$$L = \sum_{i=1}^{n} \sum_{\omega=i}^{i} \log\left(\Phi\left(\alpha_i - \beta' x\right) - \Phi\left(\alpha_1 - \beta' x\right)\right).$$

We have used the oprobit command in Stata version 13.0 to estimate the ordered probit model. Thereafter, marginal effects were calculated to determine the magnitude by which each independent variable alter the likelihood of respondents in each of the five categories of the response variable. According to Chen et al. (2002) and Liao (1994), marginal effects for ordered probit model can be obtained as:

$$\frac{\delta(\omega_i = j)}{\delta x_n} = \left[\Phi\left[\alpha_{j-1} - \sum_{\alpha-1}^{\alpha} \beta_n x_n \right] - \Phi\left[\alpha_j - \sum_{\alpha-1}^{\alpha} \beta_n x_n \right] \right] \beta_n$$

And j is the number of CSA technologies that a farmer is practicing.

RESULTS AND DISCUSSION

Characteristics of the farm households

Out of the 428 farmers sampled, 39.9% reported that they were not using any CSA strategy in their agricultural production, whereas 17.9, 15.3, 28.3 and 4.3% of the farmers reported that they had adopted one, two, three and four CSA practices, respectively. Overall, there seems to be a problem with CSA extension service availability in the study area as only 32.4% of the farmers reported to have accessed climate smart agriculture related extension services, 12 months preceding this survey.

Mean age of household heads was 44.6. Analysis of variance shows that there are no differences in ages between and among farmers who reported to have adopted various numbers of CSA technologies (Prob>F= 0.4120). A majority of household heads (62.2%) reported to have obtained some primary level education while 26.7% of the heads reported to have attended secondary school with 10% reporting to have no formal education at all.

On average, households had a mean annual income of MK223, 257.00 (US$465.12 at 2013 exchange rate). One way analysis of variance shows that there are no differences in total household incomes among and within farm households that adopted various numbers of CSA practices (Prob>F=0.2544).

Farmers in the study area seem to cultivate small pieces of land (mean area cultivated in 2012/13 was 2.0 acres). No significant differences were found in acreage cultivated in the sample among smallholder farmers who adopted various climate smart agriculture techniques.

Adoption of the technologies

As aforementioned, the CSA strategies considered in this study are portfolio diversification, soil and water conservation, soil fertility improvement as well as irrigation and water harvesting techniques. From these four CSA strategies, we can obtain 24 various combinations of CSA strategies that farmers may adopt; each with its own determinants and probability of adoption.

At individual CSA strategy level, however, 35% of the respondents reported to have adopted portfolio diversification, 43.7% practiced soil and water conservation, 24.2% of the sample reported that they practiced soil fertility improvement while 31% said they practiced irrigation and water harvesting.

Generally, levels of adoption are low in the sample for all CSA strategies. Soil and water conservation is the most adopted CSA strategy with 44% of the farmers reporting to have adopted it. This may be the case because a lot of extension messages on CSA issues hover around soil and water conservation. The frequency distribution of the number of CSA technologies that farmers reported to have adopted in study area are presented in Figure 1.

Determinants of CSA technologies adoption

The model's Chi square coefficient (165.17 with 27° of freedom) is statistically significant at 1% level of probability (P<0.0001). All the threshold parameters are significant; implying natural ordering of the response variable (α_1 ,α_2 and α_3 are significant at 5% level of probability whereas α_4 is significant at 1% level of significance). Wollni et al. (2010) posit that the coefficient estimates of the ordered probit model are not easily interpretable. Instead, they did recommend to concentrate on the marginal effects after estimating the ordered probit model. To understand how each independent variable changes the probability of adopting the number of CSA technologies given the covariates, an increase in age of the household head reduces the probability of adoption of more than two CSA practices by 4.5% (Table 2). This is in agreement with what Teklewold et al. (2013) found in Ethiopia. An increase in age of the household head was speculated to reduce the probability of adopting more than two CSA technologies, because as farmers advance in age, they tend to minimize activities that demand much of their labour and management skills. Further, due to experience with climate-related shocks over years, older farmers acquire indigenous knowledge that allow them to be relatively resilient to shocks than younger farmers such that they find it convenient to rely on their indigenous knowledge than adopt modern practices that may have steep learning curves (Nyong et al., 2007).

Holding all factors constant, an acre increase in area of total land owned reduces the probability of adopting more than two CSA practices by 11% (Table 2). Generally, increasing the area that a typical smallholder farmer controls would entail introducing additional costs to the

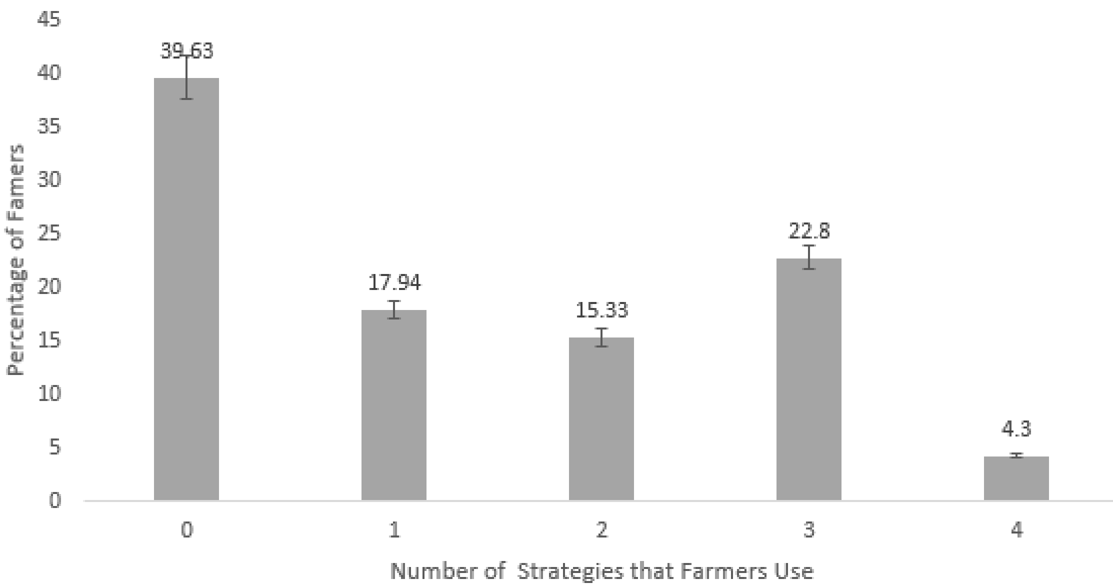

Figure 1. Percentage of farmers adopting various numbers of CSA practices.

farmer which they may fail to cover given their resource base. The probability of adopting more than two CSA strategies has a 15% increase for every additional acre. This result makes sense when one considers how resource constrained smallholder farmers are to manage a lot of climate-smart technologies on a bigger plot of land.

The status of being a lead farmer[1] was used as a proxy for ample access to CSA extension messages given that most Non-Governmental Organizations (NGOs) in the study area are training and using lead farmers to drive adoption of CSA practices. As expected, the marginal effects show that being a lead farmer, as opposed to being regular/follower farmer, increases the probability of adopting more than two CSA practices by 36% (Table 2). This result implies that ample access to extension services can help get many farmers adopt a mix of CSA technologies that can make their agricultural production system more resilient and sustainable.

For those who reported not being employed during the survey, being a petty trader increases and being formally employed reduces the probability of adopting more than two CSA strategies by 21 and 34%, respectively (Table 2). Although, not expected, these results make sense because farmers who have diversified their income generating activities are generally more able to handle impacts of climate-related agricultural production shocks through purchasing food, using other means, and no need to make their agricultural production more resilient. Most farmers who are involved in off farm income generating activities rarely attend CSA extension activities and this affects their probability of adopting the CSA strategies.

Farmers who observed an increase in floods in a 20 years period preceding the survey had 9% higher probability of adopting more than two climate-smart agriculture practices than those who reported not observing any increase in frequency of floods in the said 20 years period (Table 2). These were expected results given that, it is only those farmers who appreciate the risk that floods pose to their agricultural enterprise that see the need to adopt CSA practices to make them more resilient to the shocks.

Farmers who reported observing changes in moisture levels in their area during a 20year period before the survey had a 19% lower probability of adopting four CSA technologies. A positive relationship was expected between observing changes in moisture levels in the farmer's area with adoption of higher numbers of CSA practices, given the importance of moisture in agricultural production. However, the marginal effects show otherwise.

A positive and significant relationship between household income and intensity of adoption of technologies was expected, literature suggests that household income is an important driver of adoption (Katengeza et al., 2012; Wollni et al., 2010; Boz and Akbay, 2004). It was expected that higher-income households were supposed to have higher probabilities of adopting more than one CSA technology given their potential to purchase inputs that may help sustain many CSA technologies as compared to lower-income

[1] Farmers who are supported by extension service providers and NGO to provide agricultural extension services to other farmers in their communities (Franzel and Simpson, No Date)

Table 2. Ordered probit results with marginal effects.

Variables	Coefficients	Marginal effects				
		Prob(Y=0|X) dy/dx	Prob(Y=1|X) dy/dx	Prob(Y=2|X) dy/dx	Prob(Y=3|X) dy/dx	Prob(Y=4|X) dy/dx
Age of household head	-0.130** (0.0597)	.0489***	-0.005*	0.001	-0.012**	-0.032***
Age of household head square	1.646** (0.800)	-0.620***	0.065*	-0.014	0.153**	0.416***
Log of land area	-0.263* (0.145)	0.099*	-0.010*	0.002	-0.024*	-0.066*
Farmer type (lead farmer=1)	1.142*** (0.139)	-0.422***	0.042***	0.017	0.105***	0.256***
Polygamous married	0.385 (0.349)	-0.134	0.022	-0.017	0.025*	0.104
Smallholder farmer(yes=1)	-0.154 (0.141)	0.057	-0.006	0.002	-0.013	-0.035
Petty trader (yes=1)	-0.658** (0.285)	0.257**	-0.014***	-0.035	-0.075**	-0.132***
Formally employed (yes=1)	-1.409** (0.682)	0.493***	-0.0166***	-0.136	-0.149***	-0.191***
Household dependency ratio	0.0344 (0.0415)	-0.012	0.001	-0.0003	0.003	0.008
Log of land area used	0.429*** (0.143)	-0.161***	0.016**	-0.003	0.039***	0.108***
Observed change in moisture over past 20 years(yes=1)	-0.701* (0.387)	0.220**	- 0.056	0.052	-0.024	-0.19*
Observed increase in floods over past 20 years(yes=1)	0.270* (0.141)	-0.101*	0.011*	-0.003	0.024*	0.068*
Access agricultural extension(yes=1)	0.153 (0.134)	-0.0580852	0.005	-0.0003	0.014	0.037
Received climate change training	0.106 (0.130)	-0.0399444	0.004	-0.0009541	0.009	0.026
α_1			5.546** (2.669)			
α_2			6.142** (2.666)			
α_3			6.670** (2.667)			
α_4			8.032*** (2.675)			
Observations			420			
Wald chi2(27)			165.17			
Prob > chi2			0.0000			
Log pseudolikelihood			-520.22665			
Pseudo R2			0.1406			

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Marginal effects (dy/dx) calculated at the mean for continuous variables and for a discrete change from 0 to 1 for dummy variables.

households. However, this study shows that household income does not significantly affect adoption of multiple CSA practices.

CONCLUSIONS AND POLICY RECOMMENDATIONS

This paper has analyzed the determinants of multiple adoption of climate smart agricultural practices in Balaka and Nsanje districts using an ordered probit model. The results indicate that age of household head, total area of land that a household owns, being involved in petty trading and formal employment as opposed to being unemployed reduce the probability of adoption of more than two CSA strategies. Unexpectedly, it was found that farmers who reported having observed changes in moisture levels in their areas for the 20-year period prior to the survey have a lower probability of adopting four CSA strategies as compared to those who reported not observing any changes in moisture in the same time period and area.

Most importantly, the study found that being a lead farmer, which proxied ample access to climate smart agriculture extension message and training access, acreage used in agricultural production in the year preceding our survey as well as observing an increase in incidences of floods in a 20-year period prior to our study increased the probability of adopting more than two CSA strategies. Interestingly, being in polygamous marriage contract was found to increase adoption of three CSA strategies.

However, it is worth noting that the ordered probit model and the resultant calculation of marginal effects indicate that none of the socioeconomic and institutional factors that conceptually affect the number of climate smart agriculture strategies that the farmers adopt significantly affects the probability of adopting two CSA strategies. Further, the study has shown that household income does not significantly affect the adoption of multiple CSA strategies, contrary to this study expectation.

Based on the results of this study, it is recommended that all relevant stakeholders should strive to provide smallholder farmers with climate smart agriculture-related extension messages if more farmers are to adopt many CSA techniques that will make their agricultural production systems resilient to climate change.

Conflict of Interests

The authors of the study and sponsors do not have any vested interest in the findings of the study.

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Full Length Research Paper

Farming household food storage, consumption and sales decision making under price risk in northern Uganda

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This study extended the agricultural household model to explain food storage, consumption and sales behaviors of farming households in northern Uganda using two major staple grains: finger millet and beans. Using secondary data collected by the Uganda Bureau of Statistics from 782 millet and beans producing households (388 households below poverty level and 394 households above poverty level), seemingly unrelated regressions were performed and risk neutrality tests were carried out. It was found that all finger millet and beans producing households in northern Uganda were risk neutral regarding storage and sales decisions with only millet producing households below poverty line being risk averse in their consumption decisions. However, households above poverty line produced and stored more millet and beans implying that they were more food secure than households below poverty level. Therefore, strategies to boost incomes, production and prudent management of millet and beans stocks at the household level are critical for food security alleviation in northern Uganda.

Key words: Food security, household, precautionary storage, consumption, sales, price risk, Uganda.

INTRODUCTION

Numerous studies have shown that precautionary food storage behavior of households differs by income level (Jalan and Ravallion, 2001; Deininger et al., 2007; Carter and Lybbert, 2012; Michler and Balagtas, 2013). Market supply, on the other hand, depends on the volume of grain harvest which is concentrated within a few months of the year in any area, and can fluctuate widely from one year to the next depending on climatic conditions (Park, 2006). According to Ravallion (1987) and Renkow (1990), households engaged in subsistence farming do not often store food for the market, but they store for future consumption. Even when prices are anticipated to rise with a high level of certainty, such households still fail to store food to get arbitrage profits. Deininger et al. (2007) argued that the concern for food security motivates household storage even when arbitrage is unlikely to insure food

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consumption as opposed for consumption of “all other goods”. Meanwhile, better access to credit, for example, increases household food storage for arbitrage and decreases storage for food security purpose implying an overall positive or negative net effect on storage (Park, 2006; Michler and Balagtas, 2013).

Several explanations have been made to understand why many farming households from developing countries store a portion of their output at harvest or invest in storage (Walker and Ryan, 1990; Fafchamps, 1992). Although, storage is used in developed countries to transfer income in the period between two harvests, this is not a realized outcome for most farming households. A study by Stephens and Barrett (2011) found a positive effect of credit access by households on storage (mostly for arbitrage purposes). However, Lee and Sawada (2010) ascertained that increasing access to credit reduced household’s reliance on storage. The disparity in the above study results might be because Lee and Sawada’s study was based on the premise that grain storage was a form of unproductive savings that households undertook due to credit constraints. Arguments on inadequacy of rural capital markets seem unsatisfactory as households could still transfer income to the planting season in the form of sales cash stored-away, so long as there are functional commodity markets. The scope for the more plausible reason of inter-temporal price arbitrage is limited to farming households with marketable surplus (mostly commercial and not subsistence farmers), and absence of marked seasonal fluctuations in crop commodity prices in some developing countries (Walker and Ryan, 1990).

The importance of food security considerations in explaining household storage inventories in developing countries has been emphasized by a number of researchers. Ravallion (1987) noted that “positive stocks are observed even when expected future price falls short of spot price plus marginal storage cost”. The report adds that “…stockholders are also likely to have viewed their stocks as a desirable precaution…” Renkow (1990) expounds on this “food security” reason by attempting to model on-farm storage decisions under price risk. Results showed that even if there is no scope for price arbitrage ($\Delta P_t = 0$), positive stocks may be held due to the “food security” motive (Renkow, 1990). Only in the case of large farming households is there evidence of significant arbitrage motives for holding food stocks (*Ibis*).

In view of these shortfalls, Saha and Stroud (1994) developed an agricultural household model of consumption, storage, savings and labour decisions expanding the reasons for crop storage under price risk beyond speculative behaviour alone, as the commodity arbitrage proponents. Particularly, for small farming households, food storage is usually motivated by their aversion to risk and food security considerations. Despite new insights into the economics of storage, this study used crop production levels to categorize sorghum farmers. Since income plays a critical role in household food security and risk-bearing in many developing countries, it perhaps would have been more meaningful to categorize the farming households using income rather than crop production levels.

In Uganda, most households usually sell off their grain surpluses immediately after harvest, rather than during the off-season when prices are high due to lack of money and proper storage facilities (APS, 1994; Owach, 1998; FAO, 2000). This household behaviour arguably could be the cause for incessant food insecurity and poverty in rural areas among other factors. Of all regions, northern Uganda is the worst hit with chronic poverty levels reaching 26% as compared to the national average of 18% (UBOS, 2015).

Therefore, the motivation of this study was to extend Saha and Stroud’s agricultural household model to explain food storage behavior of farming households in northern Uganda using two major staple grains: millet and beans. In this study, households were categorized into two based on income: households above poverty line and households below poverty line. It was anticipated that findings from this study would have policy implications on alleviation of household food and income security in northern Uganda.

ANALYTICAL FRAMEWORK

When households anticipate that price increases will be sufficient to cover real costs of storage, they tend to store food. In this case, the typical condition for strictly positive optimal storage would be:

$$\psi E_t [\tilde{p}_{t+1}] > p_t + c \qquad (1)$$

Where: ψ = intertemporal discount rate; E_t = expectations; subscript (t) = current period; p_t = current price; $\tilde{p}_{t+1}$ = next period price; c = unit storage cost. In Equation 1, a positive storage level will occur only if the expected discounted future price $\psi E_t [\tilde{p}_{t+1}]$ is greater than the spot price (p_t) plus unit storage cost (*c*). In Equation 1, commodity storage greater than zero will occur only if the expected discounted future price $\psi E_t [\tilde{p}_{t+1}]$ is greater than the current price (p_t) plus the unit cost of storage (*c*).

Within agricultural economic cycles, it is common knowledge that optimal choices in agricultural household models are not “separable” in situations of price risk (Sadoulet and de Janvry, 1995; Singh et al., 1986). For the case of subsistence farmers, their optimal choices are not separable because they are both consumers and producers of their own produce. In this study, the model developed by Saha and Stroud (1994) where farm household maximizes a time-wise additively separable and time-invariant utility function over a time horizon of T periods is followed thus:

$$\text{Max } U(.) = \Sigma \psi^t U(C_t, O_t, R_t) \qquad (2)$$

Where: U = utility; C_t = food consumption; O_t = consumption of “all other goods”; R_t = consumption of leisure. Household’s optimal choices are made in situations of production and price risk. Thus at period (t), the price at (t+1), given by ($\tilde{p}_{t+1}$) is not known to the farmer.

Following Saha and Stroud (1994), it is assumed the stochastic process ($\tilde{p}$) is a stationary Markov process, thus the probability distribution of ($\tilde{p}_{t+1}$) is conditional only on (p_t) and not the whole history of the process. Considering these assumptions, the household's optimisation problem is

$$\text{Max}_{zt}\ H = U[C,\ p_t M_t + \Delta b_t....+A_t(L_t) - c(S_t)\ l_t\ (L_t\ )] + \psi E_t[V^{t+1}\ (\tilde{p}_{t+1,}\ \tilde{y}_{t+1}\ )] \quad (3)$$

Where: H = optimal household choices (storage, consumption, sales, labour); C=optimal consumption choice; p_t = current period price; M_t = current period sales; b_t = household savings; A_t = household's net labour income [≡ off-farm labour earnings minus farm labour (hired and family) expenses]; l_t = Leisure; L_t = optimal labour choice [L_t ≡ (hired and family farm labour]; c=inventory cost; S_t = current period optimal storage; z_t ≡ [$C_{t,}$ L_t b_{t+1}, S_t] denotes the vector of decision variables to be optimally chosen by the household; E= expectation operator at period (t). $V^{t+1} = \sum^{T}_{i=t+1}\psi^{i}\ U[C^*_{i,,}\ y^*_{i,,}l_i(L_t)]$ denotes the value function, where (*) superscripts indicate optimal choices; $_y$ = Household income. Since $\tilde{p}_{t+1}$ is unknown to the household at period (t), the value of the function is stochastic, denoted by $V^{t+1}[\tilde{p}_{t+1,}\ \tilde{y}_{t+1}]$.

Saha and Stroud (1994) showed the first order conditions of Equation 3, with optimal choice vector, $z_t^* = [C_t^*,\ L_t^*,\ b_{t+1}^*,\ S_t^*]$ to be:

$$Hc_t \equiv Uc_t - p_t\ Uy_t \equiv 0 \quad (4a)$$
$$H_{Lt} \equiv [p_t\ Q_{tLt}\ (L_t\ ) + A_{tLt}\ (L_t\ )+)]U_{yt} + l_{yt}\ (L_t\ )U_t \equiv 0 \quad (4b)$$
$$Hb_{t+1} \equiv -Uy_t + (1+r)\ \psi E_t[Vy^{t+1}] \equiv 0 \quad (4c)$$
$$HS_t \equiv -[p_t + C'(S_t)]\ Uy_t + \psi E_t[V_y^{t+1}\ \tilde{p}_{t+1}] \equiv 0 \quad (4d)$$

Where all alphabetic subscripts, except the subscript t, denote partial derivatives and 0 is the null vector of the appropriate dimension.

Estimation of the model

Following Saha and Stroud (1994), the econometric model used to explore the influence of income and other factors on quantities of millet and beans stored, consumed and sold by households in northern Uganda took the form of a system of three simultaneous equations on storage, consumption and sales. The assumption that household's optimal choices are made in an environment of output price uncertainty implies that at period (t), price at t+1, represented by $\tilde{p}_{t+1}$, is not known to the household. It is assumed that the stochastic process, $\tilde{p}$ follows a stationary Markov process, hence the probability distribution of $\tilde{p}_{t+1}$ is conditional on only p_t, and not on the whole history of the process (Saha and Stroud, 1994). Optimal (Pareto optimality) household choices are therefore defined by:

$$V_t\ (\Phi) \equiv [C_t\ (\Phi),\ S_t(\Phi),\ M_t(\Phi)] \quad (5)$$

Where: V_t = optimal household choices; Φ = parameter vector of optimal choice; C_t (Φ), = optimal consumption choice; S_t(Φ) = optimal storage choice; M_t(Φ) = optimal sales choice.

Equation 5 gives the dependent variables of the complete system. Equation 6 gives the dynamic relationship of dependent and independent variables. It was assumed that household optimal savings (b_{t+1}), are subsumed in income in each period. From first-order conditions, optimal choices are functions of current crop price, moments of the distribution of random expected future price, price of substitutes and complements, income, education and gender of household head, location and poverty status of household as shown in Equation (6) below:

$$\pi \equiv [p_t,\ E(\tilde{p}_{t+1}),\ var(\tilde{p}_{t+1}),\ Y_t,\ P^*,\ P^{**},\ Sexhh,\ Dist,\ Educ,\ PovL,\ Extn,\ Seas] \quad (6)$$

Where, π = optimal household choice (storage, consumption and sales); $E(\tilde{p}_{t+1})$ = expected future price (measured by the structure $E(\tilde{p}_{t+1}) = \theta p_t$); $var(\tilde{p}_{t+1})$ = variance of future price (as proxy for price volatility); Y_t = current household income (Ushs); P* = vector of prices of substitutes of millet or beans; P** = vector of prices of complements of millet or beans; Sexhh = sex of household head (male =1; female = 0); Dist = district where household is located (1=Apac; 0=Arua); Educ = number of years spent in school for formal education (years); PovL = poverty line (1=households above poverty line; 0= households below poverty line); Extn = access to extension services (1=household visited by extension personnel; 0 = household not visited by extension personnel); and Seas = production season (1= first season 2009; 0 = second season 2008).

From Equation 5, the set up to estimate a system of seemingly unrelated regression equations would take the form:

$$y = \beta x + \mu \quad (7)$$

Where: y is a vector of the dependent variables (C, S, M), X is a matrix of regressors corresponding to those in Equation 5, β is a vector of parameters to be estimated, and µ is a vector of error terms. Following Saha and Stroud (1994), the structures $E(\tilde{p}_{t+1}) = \theta p_t$; and $var(\tilde{p}_{t+1}) = \theta[p_t - E(\tilde{p}_t)]^2 = \theta[p_t - \theta p_{t-1}]^2$ are then imposed on the moments of the distribution of random price, and these forms are then substituted into Equation 9. The parameter (θ) was jointly estimated from the data for households above and below poverty line. The estimation equation for storage takes the form:

$$S_t = \delta_1 + \delta_2 p_t + \delta_3\theta p_t + \delta_4\theta[p_t - \theta p_{t-1}]^2 + \delta_5 Y_t + \delta_6 PovL + \delta_7 P_{cas} + \delta_8 P_{bean} + \delta_9 Dist + \delta_{10} Sexhh + \delta_{11} Educ + \delta_{12} P_{fcas} + \delta_{13} Extn + \delta_{14} Seas + e_1 \quad (8)$$

and this simplifies to:

$$S_t = \beta_o + \beta_1 p_t + \beta_2 p^2_t + \beta_3 p^2_{t-1} + \beta_4 p_t p_{t-1} + \beta_5 Y_t + \beta_6 PovL + \beta_7 P_{cas} + \beta_8 P_{bean} + \beta_9 Dist + \beta_{10} Sexhh + \beta_{11} Educ + \beta_{12} P_{fcas} + \beta_{13} Extn + \beta_{14} Seas + e_1 \quad (9)$$

Where:

(9a) $\beta_o = \delta_1$
(9b) $\beta_1 = \delta_2 + \delta_3\theta$
(9c) $\beta_2 = \delta_4\theta$
(9d) $\beta_3 = \delta_4\theta^3$
(9e) $\beta_4 = -2\delta_4\theta^2$

and, S_t = current period optimal storage (in kg); β_o to β_{14} = estimation coefficients for the respective variables; p_t = current period millet price (in Ushs per kg); p^2_t = current price squared (in Ushs); p^2_{t-1}= lagged price squared (in Ushs); $p_t p_{t-1}$ = current price times lagged price (in Ushs); P_{cas} = current period cassava price (in Ushs per kg); P_{fcas} = current period fresh cassava price (in shs per kg); P_{bean} = current period beans price (in shs per kg; e_1 = error term. Other variables are as defined in equation (6).

The structure of the optimal consumption equation was

$$C_t = \alpha_o + \alpha_1 p_t + \alpha_2 p^2_t + \alpha_3 p^2_{t-1} + \alpha_4 p_t p_{t-1} + \alpha_5 Y_t + \alpha_6 PovL + \alpha_7 P_{cas} + \alpha_8 P_{bean} + \alpha_9 Dist + \alpha_{10} Sexhh + \alpha_{11} Educ + \alpha_{12} P_{fcas} + \alpha_{13} Extn + \alpha_{14} Seas + e_2 \quad (10)$$

Where C_t= optimal consumption of crop in current period (in kgs); α_o to α_{15} = estimation coefficients for the respective variables; e_2= error term. Other variables in the consumption equation are as defined in Equation 9 above. The optimal sales equation is given by

$$M_t = \gamma_o + \gamma_1 p_t + \gamma_2 p^2_t + \gamma_3 p^2_{t-1} + \gamma_4 p_t p_{t-1} + \gamma_5 Y_t + \gamma_6 PovL + \gamma_7 P_{cas} + \gamma_8 P_{bean} + \gamma_9 Dist + \gamma_{10} Sexhh + \gamma_{11} Educ + \gamma_{12} P_{fcas} + \gamma_{13} Extn + \gamma_{14} Seas + e_3 \quad (11)$$

Where M_t = current period sales (in kg); γ_o to γ_{15} = estimation coefficients for the respective variables; e_3 = error term. Other variables in the sales equation are as defined in Equation 9 above.

Under risk neutrality, household optimal choices of millet or beans storage, consumption and sales would be unaffected by changes in the second moments of random its price. Thus, the coefficients of the quadratic price regressors, p^2_t , p^2_{t-1} and p_tp_{t-1} are tested under the joint null hypothesis for risk neutrality given by,

$$H_o: \beta_2 = \beta_3 = \beta_4 = 0 \quad (12)$$

Where: β_2, β_3 and β_4 are coefficients of the quadratic price regressors ($\beta_2 = \delta_4\theta$; $\beta_3 = \delta_4\theta^3$ and $\beta_4 = -2\delta_4\theta^2$).

DATA

This study used secondary data collected by Uganda Bureau of Statistics (UBOS) during 2008/2009 agricultural census. UBOS used a stratified two-stage sample design for small and medium-scale households. The first-stage involved selection of enumeration areas (EAs) with probability proportional to size (PPS). The second stage involved selection of households (ultimate sampling units) using systematic sampling, after stratification based on acres of cropland (UBOS 2010). The total UBOS sample size for the two study districts, Arua and Apac, was 1,090 households. Using the UBOS (2010) national poverty line equivalent to Ushs 62,545 (approx. US$34) per month per adult equivalent (in 2005/06 prices), these households were categorized into two: households below and above poverty level. After data was cleaned, only 782 households (388 households below poverty level and 394 households above poverty level) were usable in this study.

The following household data were obtained from UBOS for two crop production seasons (second season 2008 and first season 2009): quantities of finger millet and beans produced, stored, consumed and sold by households, household's income; current and lagged crop prices of finger millet and beans; prices of substitutes and complements; level of education, age and gender of household head; household access to credit, extension services, and membership to farmers' group/association. In addition, household size was computed based on consumption conversion factors of adult-equivalent recommended by World Health Organization (WHO) guidelines (Appleton 2001).

During data analysis, a seemingly unrelated regression (SUR) regression technique was performed to determine factors influencing quantities of millet and beans stored, consumed & sold by households to allow for non separability of household decisions. Then, household response to price risk was tested using coefficients of quadratic price regressors or post-estimation risk neutrality test.

RESULTS

Characteristics of households

Almost three-quarters of sampled households were male headed and, there was no significant difference in age and education level of household head (Table 1). Household access to extension services, credit and membership to farmer groups or associations were generally low in the study districts, although households below poverty line appeared to have had more access to these services than their counterparts. However, as expected, households above the poverty line had higher income (Ushs 70,185 per capita per month) than those below the poverty line (Ushs 38,710 per capita per month) and, this was significant at 1% (Table 1).

Household production, storage, consumption, and sales of millet and beans

Results in Table 2 show that households above poverty line stored significantly larger quantities of millet than households below the poverty line. The respective per capita per season storage of millet was 56.5 kg (24.4 kg) for households above poverty line (households below poverty line). There was no significant difference in per capita per season millet production, consumption and sales among household groups. For beans, households above the poverty line significantly produced, stored, consumed and sold significantly more beans than those below poverty line. Per capita per season millet production and sales for households above poverty line were 202.9 and 81.4 kg as compared to only 52.6 and 15.5 kg in the case of households below the poverty line. This indicates a better food security situation in households above poverty line than those households below poverty line.

Determinants of household millet storage, consumption and sale

Results in Table 3 indicate that quantities of finger millet stored, consumed and sold varied by type of household and the result was significant at 1% level in each case. Households above the poverty line significantly stored, consumed and sold more finger millet than those below the poverty line by: storage (60%), consumption (65%) and sales (57%). Education of household head was negatively associated with quantities of finger millet stored, consumed and sold. Quantities of millet consumed and sold were positively related to the price of cassava showing that millet and cassava were complementary foods. While households in Apac stored and consumed less millet than those in Arua, household millet consumption and sales in the first season of 2009 were generally lower than in the second season of 2008. As shown in Table 3, the second moments of random price of millet (p^2_t and p^2_{t-1}), price of beans, sex of household head, and access to extension services did not have a significant effect on quantities of finger millet stored, consumed and sold by households.

The hypothesis that under risk neutrality, household optimal choices of storage, consumption and sales would be unaffected by changes in the second moments of random millet price was tested as in Equation 12 above and results are shown in Table 4.

As shown in Table 4, it can be noted that finger millet

Table 1. Characteristics of millet and beans growing households in Apac and Arua Districts.

Characteristic	HHs below poverty line (n=388)	HHs above poverty line (n=394)	Overall sample (N=782)	T-statistic or chi-square
Age of household head (years)	44.7	44.8	44.8	0.0783
Sex of household head: Male (%)	82.7	74.4	78.5	8.1123***
Education of household head (years in school)	5.8	6.2	6.0	1.2452
Household size (adult equivalent)	5.6	3.1	4.3	16.2977***
Household income (Ushs/month per capita)	38,710	70,185	52,253	31.2257***
Household access to extension services (%)	30.4	18.3	24.3	15.6593***
Household access to credit (%)	10.6	4.1	7.3	12.2451***
Membership to farmer group/association (%)	20.1	9.4	14.7	17.8843***

*** = Significant at 1%; Source: UBOS, 2010.

Table 2. Per capita seasonal millet and beans production, storage, consumption and sales in Apac and Arua districts, 2008/09 (in kg)

Crop	HHs below poverty line (n=388)	HHs above poverty line (n=394)	Overall Sample (N=792)	t-statistic
Millet				
Quantity produced	116.1	181.8	152.3	3 1.3454
Quantity stored	24.4	56.5	41.9	2.4246**
Quantity consumed	59.8	86.4	74.4	1.1602
Quantity sold	31.9	38.9	36.0	0.8050
Beans				
Quantity produced	52.6	202.9	116.6	2.7219***
Quantity stored	14.0	45.8	26.0	3.3334***
Quantity consumed	23.1	75.7	45.7	4.0035***
Quantity sold	15.5	81.4	44.9	2.9116***

***, ** = Significant at 1 and 5%, respectively. Source: UBOS, 2010.

growing households above poverty line were risk neutral in their storage, consumption and sales decisions. The null hypothesis of risk neutrality for storage, consumption and sales could not also be rejected for both types of households. However, households below the poverty line were risk averse in their consumption decisions.

Determinants of beans storage, consumption and sale

As in the case of millet, households above the poverty line significantly stored, consumed and sold more beans than those below the poverty line by: storage (83%), consumption (69%) and sales (88%). Quantity of beans sold was negatively related to the price of cassava showing that millet and cassava were complementary enterprises. Also, similar to the millet case, household beans consumption and sales in the first season of 2009 were significantly lower than in the second season of 2008. However, the second moments of random price of beans (p^2_t and p^2_{t-1}), product of current and lagged bean price ($p_t\ p_{t-1}$), sex of household head, access to extension services, location of household did not significantly affect quantities of beans stored, consumed and sold (Table 5).

Just like it was done for finger millet, the coefficients of the quadratic price regressors, p^2_t , p^2_{t-1} and $p_t p_{t-1}$ under the joint null hypothesis in Equation 12 above was tested for risk neutrality of bean producing households. Results showed that the null hypothesis of risk neutrality could not be rejected for both types of households in the beans storage and sales decisions (Table 6).

The null hypothesis of risk neutrality for beans storage, consumption and sales could not be rejected for both types of households. Thus, all beans producing households irrespective of type were risk neutral when making storage,

Table 3. Determinants of quantities of finger millet stored, consumed and sold.

Variable	Parameter estimates (t-values in parentheses)		
	Storage	Consumption	Sales
Current millet price squared (p^2_t)	-0.5252 (1.070)	-0.5176 (1.130)	-0.2382 (0.470)
Lagged millet price squared (p^2_{t-1})	0.1522 (0.370)	-0.2177 (0.560)	-0.6442 (1.480)
Type of household (Above poverty line)	0.5952*** (2.920)	0.6473*** (3.400)	0.5686*** (2.670)
Current bean price (P_{bean})	-0.2626 (0.820)	0.0279 (0.090)	-0.4461 (1.330)
Current cassava price (P_{cas})	0.5621 (1.650)	0.6613** (2.080)	0.7716** (2.170)
Sex of household head (Male)	-0.3920 (1.470)	-0.3455 (1.390)	-0.2312 (0.830)
Extension visit (Yes)	0.5031 (1.900)	-0.0082n (0.030)	0.3751 (1.360)
Education of household head (years)	-0.4342** (2.930)	-0.5000*** (2.650)	-0.7610*** (3.600)
District (Apac)	- 0.7945*** (2.770)	-0.9382*** (3.500)	-0.2784 (0.930)
Season (1st season 2009)	-0.1663 (0.650)	-0.4933** (2.080)	-0.8427*** (3.170)
Constant	7.4375** (2.380)	10.5025*** (3.600)	14.0029*** (4.280)
R^2 = 0.2292 (storage), R^2 = 0.3837 (consumption), R^2 = 0.3372 (sales)			

***, ** = Significant at 1 and 5%, respectively. Source: UBOS, 2010.

Table 4. Parameter estimates for finger millet price expectations and risk neutrality test.

Equation	Coefficient/ statistic	Type of Household		
		Below poverty line (n = 388)	Above poverty line (n = 394)	All households (N = 792)
Storage	(θ)	2.6934	0.5675	0.5478
	(chi^2)	0.8500	9.0400***	3.2800
	(δ_4)	-0.0127	-2.0999	-0.9872
Consumption	(θ)	2.5013	0.6384***	0.6069
	(chi^2)	2.3700	23.7500***	15.3200***
	(δ_4)	0.0270***	-2.7149	-0.9046
Sales	(θ)	1.4108	0.7412***	1.7582
	(chi^2)	14.6100***	24.4100***	21.2000***
	(δ_4)	0.5256	-2.9049	-0.1193

Price expectation parameter, $\theta = \sqrt{B3/B2}$; Price variance parameter, $\delta 4 = B2/\theta$. Chi^2-value is for the joint hypothesis H_o: $\beta_2 = \beta_3 = \beta_4 = 0$; *** = significant at 1%.

consumption and sales decisions.

DISCUSSION

Finger millet and beans are important staple foods in northern Uganda and, their production is mainly done for subsistence purposes with only unplanned surpluses sold. These crops are grown on a seasonal basis and depending on abiotic and biotic factors, yields fluctuate by season and location. This might explain why production of millet and beans was lower in the first season of 2009 than in the second season of 2008 and, any observed disparities between study districts. Differential household resource endowments and allocation to other competing crops, such as cassava, sorghum, pigeon peas, cow peas, could have also caused variation in production, storage, consumption, and sales of millet and beans.

While this is so, previous studies have revealed that the uncertainty of future food prices and food security concerns causes more food storage as an insurance against high future price if the household has to buy back food for domestic consumption in the future (Michler and Balagtas 2013; Saha and Stroud 1994). Moreover, precautionary food storage has been found to vary with income level of households (Jalan and Ravallion, 2001; Deininger et al., 2007; Carter and Lybbert, 2012; Michler and Balagtas,

Table 5. Determinants of quantity of beans stored, consumed and sold.

Variable	Parameter estimates (t-values in parentheses)		
	Storage	Consumption	Sales
Current bean price squared (p^2_t)	0.1535 (0.220)	-0.5072 (0.760)	0.3882 (0.500)
Lagged bean price squared (p^2_{t-1})	0.7228 (0.960)	-0.9804 (1.360)	0.2385 (0.280)
Current times lagged bean price ($p_t p_{t-1}$)	-0.7064 (0.720)	0.7431 (0.800)	-0.6225 (0.570)
Type of household (Above poverty line)	0.8278*** (3.590)	0.6884*** (3.110)	0.8755*** (3.400)
Current millet price (P_{mill})	-1.5103 (1.650)	-0.1798 (0.200)	-2.4380** (2.390)
Current cassava price (P_{cas})	-0.1229 (0.340)	0.3433 (0.980)	0.0159 (0.040)
Sex of household head (Male)	-0.2334 (0.710)	-0.0379 (0.120)	-0.1375 (0.380)
Extension visit (Yes)	0.4608 (1.740)	0.1621 (0.640)	0.4044 (1.370)
Education of household head (Years)	0.2823 (1.300)	0.2673 (1.280)	0.3768 (1.550)
District (Apac)	0.0065 (0.030)	-0.2274 (1.000)	0.0868 (0.330)
Season (1st season 2009)	-0.0811 (0.370)	-0.6734*** (3.200)	-1.0670*** (4.360)
Constant	9.6890*** (2.870)	10.9809*** (3.400)	17.1925*** (4.580)
R^2 = 0.2160 (storage), R^2 = 0.2780 (consumption), R^2 = 0.3829 (sales)			

***, ** = Significant at 1 and 5%, respectively. Source: UBOS, 2010.

Table 6. Parameter estimates for beans price expectations and risk neutrality test.

Equation	Coefficient/ statistics	Type of Household		
		Below poverty line (n =388)	Above poverty line (n =394)	All households (N =792)
Storage	(θ)	1.7816	1.9607	1.2561
	(Chi^2)	3.1400	7.9500**	2.4200
	(δ_4)	0.2053	-0.2769	0.3703
Consumption	(θ)	1.1899	2.2791**	2.2456
	(Chi^2)	4.6100	12.1200***	6.4300
	(δ_4)	-0.3762	-0.2470	-0.0913
Sales	(θ)	1.5663	1.6925	0.2569
	(Chi^2)	1.5100	28.0500***	2.0900
	(δ_4)	0.2126	0.7841	2.9424

Price expectation parameter, $\theta = \sqrt{B3/B2}$; Price variance parameter, $\delta 4 = B2/\theta$. Chi^2 - value is for the joint hypothesis H_o: $\beta_2 = \beta_3 = \beta_4 = 0$; ***and ** = significant at 1 and 5%, respectively.

2013). Saha and Stroud (1994) found a positive relationship between household income and storage of sorghum in India. Similarly, a study of rice farmers in Bangladesh showed that higher income households stored a large portion (up to 20%) of total rice storage for precautionary purposes (Michler and Balagtas, 2013).

In northern Uganda, precautionary food storage was also significantly higher among finger millet and beans producing households above poverty level than their counterparts. Although, all finger millet and beans producing households in northern Uganda were risk neutral in their storage and sales decisions, households above poverty level seemed to be more food secure than households below poverty level. With the fact that they had more income probably enabled them to produce more millet and beans and, acquire better storage facilities for these grains.

CONCLUSION AND POLICY IMPLICATIONS

Results from this study indicate that all finger millet and beans producing households in northern Uganda are risk neutral regarding storage and sales decisions with only millet producing households below poverty line being risk averse in their consumption decisions. However, households above poverty line produced and stored more millet and beans implying that they were more food secure than households below poverty level. Therefore, strategies to boost incomes, production and prudent management of millet and beans stocks at the household level are critical for food security alleviation in northern Uganda. The establishment of minimum levels of millet and beans stocks at the household level would be a more efficient and effective policy response to any price shocks than an outright ban of household sales of these staples. For successful implementation of this policy, it will require massive promotion of use of improved storage facilities among millet and beans producing households. Using the farmer groups/associations approach, households could be mobilized and sensitized on modern millet and beans storage technologies. Moreover, household use of these improved storage technologies could be enhanced by linking them to credit and better produce markets.

Conflict of Interests

The authors have not declared any conflict of interests.

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