Post-harvest Loss and Adoption of Improved Post-harvest Storage Technologies by Smallholder Maize Farmers in Tanzania

Elizabeth R. Ngowi[*] and Onesmo Selejio[**]

Abstract

The study examines factors that influence the adoption of improved post-harvest storage technologies (IPHSTs) by smallholder maize farmers in Tanzania. The study employed a sample of 1620 observations from the National Panel Survey (NPS). Descriptive statistics indicated that 9 percent of the farmers experienced PHL and an average of 115 kilograms of maize per household is lost in various stages of post-harvest chain. Only 19 percent of farmers adopted IPHSTs. Logit regression results indicated that gender, age, harvest working days, use of hired labour and use of storage protectorant (pesticides and insecticides) had positive and significant influence on PHL. Further, quantity of maize harvested and age of households' heads had positive and significant influence on adoption of IPHSTs. Therefore, the Government and development agencies should emphasize and promote the adoption of IPHSTs by smallholder farmers in order to mitigate PHL. Provision and support of extension education to farmers through trainings and seminars and extension visits on proper crop post-harvest management, storage technologies and skills is pertinent.

Keywords: post-harvest loss, adoption, improved post-harvest storage technologies, panel data, smallholder farmers

JEL Classification: Q12, Q13, Q17, Q18, C23

[*]Department of Economics, University of Dar es Salaam, P.O.Box 35045,Dar es salaam, Tanzania Email: ngowielizabeth00@gmail.com

[**] Corresponding Author, Department of Economics, University of Dar es Salaam, P.O.Box 35045,Dar es salaam, Tanzania Email: oselejio@gmail.com

1. Introduction

Post-harvest loss (PHL) of crops is one of the major problems in Sub-Saharan Africa (SSA) that calls for the world's attention due to the focus of food security. Food security has been an elevated priority in most of the SSA countries including Tanzania since the world food crisis of 2007-2008, due to increasing population and food prices (World Bank, 2011). PHL vary among countries, crops, between seasons, between stages in post-harvest chain, and these are significantly higher among smallholder farmers in SSA with the average loss ranging from 20–40 percent (URT, 2017). Indeed, post-harvest losses in SSA occur mostly in grain crops such as maize, paddy, millet and sorghum. Crop losses that occur in storage have brought much attention to the concept of storage technologies, since they are important aspects of ensuring food security. Further, it has been noted that storage helps to stabilize fluctuations in market supply, between and within season, by taking produce off the market in surplus seasons, and releasing it back onto the market in lean seasons (Kimenju & De Groote, 2010).

Intervention of PHL is an important component of the efforts of many countries and many development agencies such as HELVETAS, AGRA and IITA to reduce food insecurity and is increasingly recognized as part of an integrated approach to realizing agriculture's full potential to meet the world's increasing food and energy needs (World Bank, 2011). Mitigation is accompanied by the invention of the improved post-harvest storage technologies (IPHSTs) so as to reduce storage losses.

Though a lot has been done on the dissemination of PHL reduction, these approaches for mitigation of PHL have had little success. Many smallholder farmers still continue with traditional storage methods and suffer losses despite huge investments in IPHSTs implying that there is poor adoption of the improved technologies (Abdoulaye *et al*., (2016). Studies on technology adoption have biased on production technologies and few studies have tried to establish causes of PHL and influence of adoption of post-harvest storage technologies (HELVETAS, 2014; Suleiman and Rosentrater, 2015; APHLIS, 2017). However, the few existing studies on adoption of post harvest technologies are mostly outside Tanzania and have used cross-sectional data which results into estimation bias because of endogeneity problems (Green, 2003; Cameron and Trivedi, 2010; Aidoo *et al*., 2014; Kidane *et al.*, 2015).

This paper examines the factors that influence the adoption of IPHSTs technologies in smallholder maize farm holdings of Tanzania using national panel survey (NPS). Specifically the study examines the determinants of maize post-harvest losses and the determinants of adopting the IPHSTs by smallholder maize farmers. The study addresses the endogeneity problems of the previous studies which used cross section data to analyse the causes of PHL (e.g. Folayan, 2013; Boateng, 2016; Adisa *et al*., 2015) and influence of adoption of improved post harvest storage technologies (e.g. Atibioke *et al*., 2012; Conteh *et al*., 2015; Abdoulaye *et al*., 2016). Also, unlike a study by Ndiritu (2013) that used one wave of NPS (NPS 2010/2011) of cross section data, this study employs 3 waves: wave I (2008-2009), wave II (2010-2011) and wave III (2012-2013).

The remainder of this study is organized as follows. Section 2 reviews the literature on Post-harvest loss and adoption of improved post-harvest storage technologies. Section 3 discusses the situation of Post-harvest losses of maize in Tanzania while Section 4 presents Methodology of the study. Section 5 presents results and discussion. Lastly, conclusion and policy implications are presented in Section 6.

2. Literature review

Post-harvest loss is defined as crop losses that occur after separation from production site to the point where the crop is prepared for consumption (Suleiman and Rosentrater, 2015; Nyambo, 1993; Boxall, 1986). Post-harvest losses are classified into three main categories; qualitative loss, quantitative loss and economic or commercial loss. Quantitative loss refers to the reduction in physical weight, and can be readily quantified and valued a good example can be a portion of grain damage by pests or lost during transportation. A qualitative loss is contamination of grain by moulds and fungus; it includes loss in nutritional quality, edibility, consumer acceptability of the products and the caloric value. Qualitative losses occur through the decreased value of grain due to spoilage caused by grain discolouration, physical contamination and spillage (Brown *et al*., 2013). Economic loss is the reduction in monetary value of the product due to a reduction in quality and/or quantity of food (Suleiman and Rosentrater, 2015; Tefera, 2012; World Bank, 2011). Generally, PHL has impact on livelihood, income, production incentive and investment (Kimenju & De Groote, 2010; World Bank, 2011; Mbwambo *et al*., 2016)

According to African Post-Harvest Loss Information System APHLIS (2017), the crop loss occurs along the post-harvest chain that includes all processes after harvest till the grain reaches the final consumer. The stages of post-harvest chain stages are harvesting, transport to the household, drying, threshing/shelling, winnowing, farm storage, transport to the market, market storage, processing and marketing (APHLIS, 2017). However, the crop loss at storage stage has drawn much attention since it accounts for large proportion of loss of grain particularly maize (Abass and Tefera, 2012; Mutungi and Affognon, 2013).

Storage losses in SSA including Tanzania are caused mainly by rodents, termites, insects, pests, birds and high crop moisture content during storage. Storage pests such as scania, LGB and sitofilus are considered to be the most destructive organisms in stored maize, whereby they contribute over 25 percent of the storage losses (Abass and Tefera, 2012). Crops stored with high moisture content are susceptible to mold and fungus growth, risk of mycotoxin and aflatoxin, and resulting in a high amount of broken grains and low milling yields (World Bank, 2011; Kumar and Kalita, 2017).

There are wide empirical evidences on determinants of post-harvest losses and factors influencing the adoption of improved technologies using different methodologies and reveal different results whereby some of them reach on the same consensus but others do not (Folayan, 2013; HELVETAS, 2014; Tadesse, 2016). However most of the existing studies have used cross-sectional data. For example Boateng (2016) employing OLS regression analysis on cross-sectional data to estimate the determinants of post-harvest loss in maize in Ghana found that the length of production, education level, household size, and duration of storage had positive influence on post-harvest loss while traditional storage indicated a negative influence on post-harvest loss. The same findings are reported by the study of Folayan (2013) in Nigeria which used the same methodology. The results from studies of Maremera (2014) and Tadesse (2016) which employed different analytical methodologies, i.e. ordered probit model and probit model respectively on cross-sectional data reveal that age, gender, storage facility, farming experience and distance to the market had significant influence to post-harvest losses in South Africa and Ethiopia.

One the other hand, many studies on determinants that influence the adoption of crop storage technologies, in different countries, have shown that education, household size and cultivated grain type, age, farm size, farming experience, number of dependents and contact with extension agents had significant influence on adoption (Atibioke et al. 2012; Nasiru, 2014; Conteh et al. 2015). In Tanzania, Ndiritu (2013) studied on post-harvest food loss abatement technologies particularly rural Tanzania. But the study used a cross-section data from NPS 2010/2011 and employed a bivariate probit model regression. The finding from this study indicate that climatic conditions (rainfall, temperature) and amount of maize harvest had positive influence on adoption of preservation techniques while distance to the nearest road (used as a proxy for higher cost of acquiring the preservation method) had negative influence on adoption preservation techniques. and amount of maize harvest had positive influence on adoption of preservation techniques

Although previous studies have highlighted the causes of crop post-harvest loss and determinants of adoption of post-harvest storage technologies, but most studies have been done outside of Tanzania using cross-sectional data which leads to estimation bias because of endogeneity problems which cannot be controlled using the cross-sectional data estimation methods [1]. In this case the results may not be conclusive for effective policy implication. Thus, the current study addresses the weaknesses of the previous studies by using the national panel data in Tanzania context.

3. Post-harvest losses of maize in Tanzania

Tanzania is one among the SSA that suffers from persistent food shortages, and this is as the results of post-harvest losses especially in the semi arid areas such as Singida and Dodoma, coastal regions such as Mtwara, Tanga, Lindi and Coast region and some areas of Kigoma, Shinyanga, Mara and Morogoro (Mutungi and Affognon, 2013). Smallholder farmers in Tanzania lose up to 40 percent of their harvest (Tanzania markets-PAN, 2013). Like in any other SSA countries, maize grain is the crop with the highest PHL in Tanzania. This is due to the reasons that maize is the key dietary and staple crop for a large populace of households in Tanzania (Wilson and Lewis, 2015)

During the 1950s-1960s at the initial state of grain losses, Tanzanian government, nevertheless, did not show support to farmers on the problem of post-harvest losses due to the reason that there was lack of comprehensive data on PHL in grain in the country. Until the 1970s, Tanzania did

[1] Conteh *et al.*, (2015) studied the determinants of grain storage technology adoption promoted by SLARI in Sierra Leone using cross-sectional data and logistic regression model for analysis. Atibioke *et al.*, (2012) analyzed the effects of farmers' demographic factors on adoption of grain storage technologies particularly hermetic storage, grain stores, maize crib and polypropylene lined bags using a cross-sectional data collected from a sample of 120 farmers in Kwara state, Nigeria and logistic regression model.

not impose policy on storage for agricultural products; however, following the appearance of the Large Grain Borer (LGB) in the 1980s, resulting in post-harvest losses of cereals, which endangered food security in the country, the government began to support farmers to reduce post-harvest losses (Mutungi and Affognon, 2013).

Table 1 presents the trend of estimated maize post-harvest losses[2] in Tanzania in percentage and tones of the total annual production from 2003 to 2012. High PHL from 2003-2007 resulted due to poor policy implementation. After the food crisis of 2007-2008 various policies were introduced such as the agricultural marketing policy of 2008 which raised the awareness of PHL so as to ensure food security. The policies advocated for use of improved crop post harvest handling and storage technologies such as drums, silos, cribs, Purdue Improved Crop Storage (PICS) bags, Hermetic cocoons and Warehouse Storage (URT, 2003; Kimenju and De Groote, 2010; AGRA 2014; Chegere, 2017). This resulted to the decline of PHL in 2008, however implementation of these polices and strategies became subject of failure because of poor adoption of the improved post-harvest handling techniques leading to the persistency of high PHL.

This high post harvest loss has forced most smallholder farmers to sell their crops at low prices soon after harvest so as to avoid storage losses. as the result they buy back at an exorbitant price just few months after harvest, ending up into a poverty trap.

Table 1: Estimated Maize Post-Harvest Losses in Tanzania. (In Tons and Percentage of the Total Production) 2003-2012

Years	PHL (%)	PHL (t)
2003	22.1	739,450
2004	22.2	714,444
2005	22.2	770,626
2006	22.2	732,382
2007	22.2	796,985
2008	17.5	392,818
2009	17.4	755,291
2010	17.9	410,882
2011	17.7	718,691
2012	17.6	905,425

Source: African post harvest losses information system (APHLIS), 2017

4. Methodology

4.1 Study area and Sample

[2] PHL is estimated by APHLIS as dry weight loss in all stages of the post-harvest chain (value chain)

The coverage of the study is national-wide as it used secondary data from Tanzania national panel survey (NPS) which included three waves which are; wave one (2008-2009), wave two (2010-2011) and wave three (2012-2013). The NPS data are collected by the National Bureau of Statistics (NBS) in collaboration with the Ministry of Agriculture, Food Security and Cooperatives (MAFSC). NPS is a national wide survey which used a representative sample from each region in Tanzania.

The study focused on smallholder maize growing households. The study based on maize crop since it is the dominant cereal crop grown in Tanzania and facing the highest PHL. Furthermore, the smallholder farmers are the leading populations that engage in maize production in Tanzania. The study survey collected detailed information about the standard of living of the population and particularly their agricultural characteristics. A sample of 1620 observations or households of smallholder maize farmers was extracted for this study from the main NPS data. In each wave a total number of 540 observations were obtained.

4.2 Theoretical Framework of the Technology Adoption and PHL Model

Theoretical framework presents models employed in the adoption of the IPHSTs and PHL model. It also presents appropriateness of the models for the study. The empirical models of adoption of IPHSTs and PHL are derived from the random utility of an individual. The random utility theory is given algebraically as;

$$U_{in} = V_{in} + \varepsilon_{in} \quad (1)$$

Where;

U_{in} is the unobservable true utility of an individual n for choosing i
V_{in} is the systematic (deterministic) component of utility of an individual n for choosing i
ε_i is the random (stochastic) component of utility of an individual n for choosing i

Assuming there are two utilities say U_{in} *and* U_{jn}, an individual will choose U_{in} if and only if $U_{in} > U_{jn}$ $\forall j \neq i$ from the choice set C_n whereby n is an individual decision maker, i and j are choices. And since the researcher cannot observe an individual's utility as it comprises of a random element (component), therefore a researcher can just predict the probability that an individual n will select an alternative i (but an alternative may not be exact). The probability is written as $p\left({}^{i}/_{C_n}\right) = pr(U_{in}) \geq U_{jn}, \forall j \varepsilon C_n$ (Wittink, 2011).

Taking into account a binary choice model of this study that consists of only two alternatives namely *adoption of IPHSTs* and *not adopting the improved post-harvest technologies,* and considering that in post-harvest chain farmers are faced with risk of PHL either during harvesting, transport, storage or marketing, regardless of their adoption or non-adoption of the IPHSTs, two alternatives are generated which are *experienced post-harvest loss* and *non-experienced* .The probabilistic choice model can be derived and estimated by the binary Logit or Probit models. These models overcome problems of linear probability models exceeding the 0-1 interval as well as constant marginal effect (due to a linear relationship between probability and explanatory variables).

Furthermore, Logit or Probit models are opted to estimate the probabilistic choice model because linear regression models require strict adherence to assumption of classical linear regression model (CLRM) such as normality, linearity, equal variance and covariance of error term, and a questionable value of R as the measure of goodness of fit (Gujarati, 2004). Therefore Logit and Probit models have become appropriate models to use since such assumptions of CLRM need not to be fulfilled (Hair *et al*, 2006).

Generally, Probit and Logit models are the same yet differ in the assumptions imposed on the distribution of their error terms. For the case of Logit model, error term is assumed to have a cumulative standard logistic distribution while in probit model, the error term is assumed to have a cumulative normal distribution (Greene, 2003), but the results obtained from both models tend to be more or less similar.

In order to analyze such binary dependent variables for this study, a binary logit model is set to be the best choice. This approach is chosen as a matter of convenience as it provides meaningful interpretation and simpler in estimation (Pindyck and Rubinfeld, 1981). Furthermore, there is no theoretical justification of selecting one approach over the other (Maddala, 1987)

4.3 Empirical specification and Estimation

The Empirical specification and estimation technique of the Technology Adoption and PHL Model adopts the following the logit model:

$$L_i = Ln\left(\frac{P_i}{1-P_i}\right) = Z_i = \beta_0 + \beta_1 X_i$$

Specifically, the Marginal Maximum Likelihood (MML) method is used to estimate the parameters. The objective of Maximum Likelihood (ML) is to maximize the Likelihood Function (LF) or the Log Likelihood Function (LLF) (Gujarati, 2004). In this study, Random Effect (RE) or Fixed Effect (FE) Logit model is applied to quantify the combined factors influencing the adoption of IPHSTs as independent variables as well as gauge the role of each variable in explaining the variation in the dependent variable so as to meet the objective of the study. Logit model is specified as:

$$Pr(y_{it} = 1) = \beta_0 + \beta_1 age_{it} + \beta_2 gender_{it} + \beta_4 hsize_{it} + \beta_5 marstat_{it} + edu_{it} + \beta_6 fsize_{it} + \beta_7 lnharvest_{it} + \beta_9 lnfoodexp_{it} + \beta_{10} extens_{it} + \alpha_i + \varepsilon_{it} \quad (2)$$

Random Effect (RE) or Fixed Effect (FE) Logit model is also applied to quantify the collective factors that have influence on PHL as independent variables. Moreover, the Logit model is used in determining the role of each variable in explaining the variation in the dependent variable so as to meet the objective of the study. Logit model is specified by equation below;

$$Pr(y_{it} = 1) = \beta_0 + \beta_1 gender_{it} + \beta_2 marstatus_{it} + \beta_3 lnworkdays_{it} + \beta_4 hlabour_{it} + \beta_5 lnplot\_market_{it} + \beta_6 storageprot_{it} + \alpha_i + \varepsilon_{it} \ldots \quad (3)$$

For the model used to determine factors that influence adoption of IPHSTs (Equation 2), y_{it} is a dependent dummy variable whereby D=1 if farmer has adopted IPHSTs which include all who have adopted improved locally made structures, modern store, airtight drums, and sacks/open drum and D=0 for not adopting IPHSTs which include all those who have adopted locally made traditional structure, unprotected pile, ceiling and other.

For the model used to determine factors that influence crop PHL (Equation 3), y_{it} is a dummy variable whereby D=1 if farmer experienced PHL and D=0 if farmer did not experience PHL. This loss comprises all losses reported by farmer experienced in the post-harvest chain from harvesting stage to marketing in that given year (t).

The independent variables include in models are Age_{it} is Age_{it} of the head of the household head (years); $gender_{it}$ is gender of household head (1 = male, 0 = female); edu_{it} is number of years in school of household head (number); $hsize_{it}$ is household size (number); $farmsize_{it}$ is farm size (acre); $martstat_{it}$ is marital status of the household (1 = married, 0 = otherwise); $harvest_{it}$ is quantity of maize harvested (kg $foodexp_{it}$ represents food expenditure (TSH); $extension_{it}$ is access to extension services (1 = yes, 0 = otherwise); $workdays_{it}$ is number of days spent for harvesting of maize (number); $hdlabour_{it}$ is whether a household hired labour during harvesting (1 = yes, 0 = otherwise); $plot\_market_{it}$ represent distance from plot to market (km); and $storageprot_{it}$ is whether the household used storage protectorant (1 = yes, 0 = otherwise)

Hausman test to determine the appropriate model between the fixed effect model (FEM) and the random effect model (RFM) was performed. The null hypothesis underlying the Hausman test is that the FEM and REM estimators do not differ substantially, i.e. Coefficients estimated by the efficient random effects estimator are the same as those estimated by the consistent fixed effects estimator. According to Cameroon and Trivedi, (2010), the statistic developed by Hausman has an asymptotic $\chi 2$ distribution, i.e., if the null hypothesis is accepted which is implied by an insignificant p-value, the conclusion is that REM is more appropriate. And when the null hypothesis is rejected i.e. p-value is significant and FEM should be used

4.4 Data Type, Source, Scope and Coverage

The study used secondary data obtained from three waves of the National Panel Survey (NPS) which are; wave one (2008-2009), wave two (2010-2011) and wave three (2012-2013). The NPS data are collected by the National Bureau of Statistics (NBS) in collaboration with the Ministry of Agriculture, Food Security and Cooperatives (MAFSC). NPS is a national wide survey which used a representative sample from each region in Tanzania. The study survey collated detailed information about the standard of living of the population and particularly their agricultural characteristics. A sample of 1620 observations or households of smallholder maize farmers was extracted for this study from the main NPS data. In each wave a total number of 540 observations were obtained. This sample covered only household heads who cultivated maize.

5. **Results and discussion**

5.1 Descriptive statistics

Table 2 indicates the summary statistics of the variables used in the model. Most of the household heads were males (77 percent). The average age of household heads was 50 years. Among the total household heads observed, 77 percent were married and majority of the household heads had attained primary school education level since mean years in school was 8.5. The average household size of the smallholder maize farmers was 6 and average food expenditure for smallholder farmers per month was TShs 60,058/=. The statistics do not differ much with that of National Population Census and National Sample Census of Agriculture 2008 which show that the average household size is 5.2 persons and 5.3 persons respectively (URT, 2012 ; URT, 2013).

Table 2: Description and Summary Statistics of Variables

Variable	Observation	Mean	Std. Deviation	Minimum	Maximum
Dependent variables					
Storage technology (improved=1)	1620	0.19	0.391	0	1
Post-harvest loss (Yes=1)	1620	0.09	0.286	0	1
socio-economic variables					
Age (Years)	1620	49.74	15.387	19	92
Gender (Male=1)	1620	0.77	0.421	0	1
Marital status (Married=1)	1620	0.755	0.431	0	1
Education level (number of years in schooling)	1620	8.51	2.09	1	19
Household size	1620	5.98	2.852	1	35
Food Expenditure (Tsh)	1620	60058.11	55264.03	2000	543200
Farm related characteristics					
Farm size(Acre)	1620	5.39	5.31	2	80
Harvest(Kg)	1547	532.76	660.096	15	4800
Extension service (Yes=1)	1620	0.12	0.33	0	1
Access to credit (Yes=1)	1620	0.01	0.11	0	1
Post-harvest related characteristics					
Hired labour (Yes=1)	1581	0.28	0.448	0	1
Harvest working days(Days)	1620	41.96	44.81	1	280
Storage quantity (Kg)	460	303.7	332.827	5	1800
Storage protectorant (Yes=1)	1620	0.20	0.40	0	1
Distance: plot to market(Km)	1620	11.15	10.763	1	112
PHL(kg)	144	114.63	156.26	4	840

Source: Author's construction (2017) from national panel survey data

The average area cultivated was 5 acres and the average output of maize harvested per area cultivated was 533 Kilograms. The average amount of maize that the farmers have in storage was 304 kilograms. Only 9 percent of the smallholder farmers have experienced PHL and 115 kilogram of maize on average was lost in various stages of post-harvest chain. Only 1 percent and 12 percent of the smallholder farmers have access to credit and extension services respectively. Smallholder farmers who adopted IPHSTs and used storage protectorant comprised of 19 percent and 20 percent respectively. On average household use 42 days[3] (equivalent to average of 7 days per each member of the household) on harvesting and 28 percent of the famers hired labour during harvest. The average distance from farm plot to the nearest market is 11km.

5.2 Households Characteristics Effects on Post-Harvest Loss and Adoption of IPHSTs

a) Gender

Table 3 shows the relationship between gender of households' heads and post harvest loss and adoption of IPHSTs. The findings indicate that majority of the male headed households experience post-harvest loss but are main adopters of IPHSTs. The results from Chi-square test indicate that there is significant association between gender of households' heads and postharvest loss (p=0.00) and the relationship between gender of households' heads and adoption of IPHSTs is not significant (p=0.76).

Table 1: Post-Harvest Loss, Adoption of IPHSTs and Gender of Household Head

Variable		Gender of Household Head		Pearson chi2 value	p>|z|
		1=Yes	0=Otherwise		
Post-harvest loss	1=Yes	86.81	13.19		
	0=otherwise	76.27	23.73	8.2704	0.00***
	Total	1237	365		
Adoption of post-harvest storage technologies	1=improved	77.7	22.3		
	0=otherwise	76.88	23.12	0.0947	0.76
	Total	1248	372		

*, ** and *** imply 10 percent, 5 percent and 1 percent respectively.

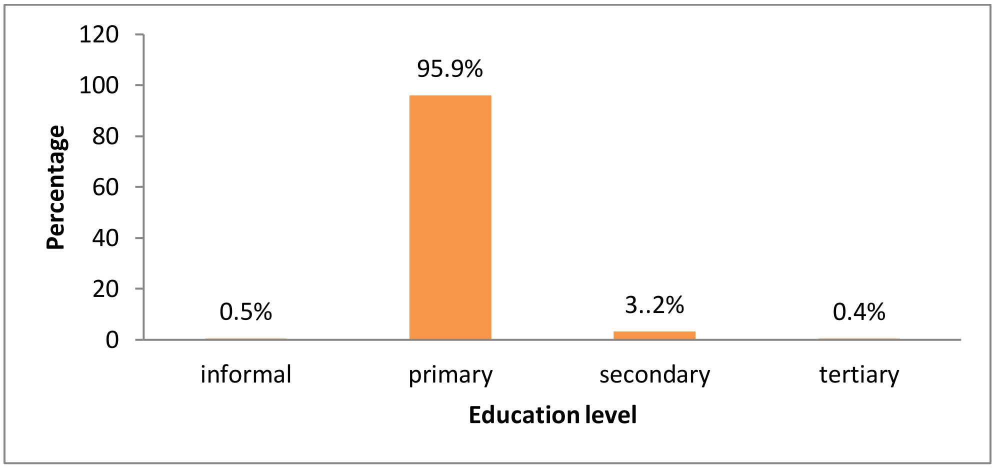
Source: Author's construction from NPS data (2008/2009, 2010/2011, 2012/2013).

b) Level of education

Figure 1 demonstrates the level of education of the households' heads. Majority (95.9%) of the households' heads have primary education level and followed by households' heads secondary education level with (3.2%). Only 0.4% of the heads of households have tertiary education level while 0.5% have informal education. Findings imply that education is not among the foremost important thing among the rural people due to few/lack of schools beyond primary level and those few are located in far distances from homesteads leading to school dropout. Similar findings by HELVETAS and ANSAF (2016) indicated that 90 percent of the respondents have education between none and primary education.

[3] Average number of days (7 days) spent by an individual in harvesting is obtained by diving total average days (42 days) spent by household in harvesting by the average household size(6)

Figure 1: Households' Heads Level of Education



Source: Author's construction from NPS data (2008/2009, 2010/2011, 2012/2013).

Table 4 shows the relationship between education level and adoption of post-harvest storage technologies. Findings indicate that households' heads with primary education level are the most adopters of IPHSTs. Further analysis using chi-square test indicate (p=0.03), implying there is a significant association between education level and adoption of IPHSTs.

The findings indicate that majority have attained primary education level whereby majority of them are non-adopters of IPHSTs as compared to adopters of IPHSTs. Findings imply that low level of education has impact on adoption of IPHSTs because low levels of education hinder farmers' access to knowledge on post-harvest handing procedures. Study by Saha et al., (1994) supports the findings that there is a positive relationship between education level and households' adoption behaviour. The study also complies with that of Bisanda et al., (1998) which reveal that most farmers in Tanzania have primary school education and hence rely on traditional farming practices.

Table 2: Adoption of IPHSTs and Households' Heads Education Level

Variable		Households' Heads Education level				Pearson chi2 value	p>|z|
		Informal	Primary	Secondary	Tertiary		
Adoption of post-harvest storage technologies	1=improved	0.00	94.75	3.93	1.31		
	0=otherwise	0.61	96.20	2.97	0.23	9.3716	0.03**
	Total	8	1554	51	7		

*, ** and *** imply 10 percent, 5 percent and 1 percent respectively.

Source: Author's construction from NPS data (2008/2009, 2010/2011, 2012/2013).

c) Access to extension services

Table 5 shows the relationship between households' heads access to extension services and adoption of IPHSTs. Findings indicate that among the households who have access to extension services, majority have adopted improved than non-adopters and among households who do not have access to extension services majority have not adopted the improved technologies compared to the adopters of improved storage technologies.

Findings imply that there are few households' heads that received extension services. This is because of few number of extension agents. Likewise, most farmers cannot access extension services due to the remoteness of the area they live. This implies that there is low ratio of extension agent/farmers in Tanzania like other developing countries (Tessema *et al*., 2018). This results to failure of extension agent to reach many farmers and hence farmers are left out without services, and lack of extension service might lead to one way or another to low adoption of the post-harvest storage technologies by smallholder maize farmers.

Similar findings have been reported by Rao and Rao (2006) that signified farmers experience in adoption is increased in relation to provision of training. Further, the results of Pearson chi square test indicates that there is no significant association between households' heads access to extension service and adoption of improved storage technologies (p=0.02).

Table 5: Adoption of IPHSTs and Households' Heads Access to Extension Service

Variable		Households' Heads Access to Extension Service		Pearson chi2 value	p>|z|
		1=Yes	0=Otherwise		
Adoption of post-harvest storage technologies	1=improved	16.39	83.61		
	0=otherwise	11.48	88.52	5.432	0.02**
	Total	201	1419		

*, ** and *** imply 10 percent, 5 percent and 1 percent respectively

Source: Author's construction from NPS data (2008/2009, 2010/2011, 2012/2013)

5.3 Econometrics results

Before choosing appropriate panel model between fixed effect model and random effect model, a Hauseman test was conducted. The results of Hausman test for Logit Regression Model on determinants of maize post-harvest loss show that the p-value is 0.3944 which is different from zero and hence insignificant. This leads to acceptance of the null hypothesis that the FEM and REM estimators do not differ substantially. Hence, the results of Hausman test suggest that random model is appropriate for this analysis. However, the p-value is 0.0000 which is not different from zero and hence significant for Hausman test for Logit Regression Model on determinants of adoption of improved post-harvest storage technologies. This leads to rejection of the null hypothesis that the FEM and REM estimators do not differ substantially, i.e. coefficients estimated by the efficient random effects estimator are not the same as those estimated by the consistent fixed effects estimator. Hence the results of Hausman test suggest that fixed effect model is appropriate for this analysis.

5.3.1 Logit regression results on determinants of post harvest loss

Results of random effects logit model show that the model is significant at 1 percent i.e. 0.0000, implying that the overall model is fit. Results show that out of six (6) independent variables, only five (5) variables were found to significantly influence PHL, these are; gender (*gender*), age, harvest working days (*lnharvest*), use of hired labour (*hlabour*) and use of storage protectorant (*stogeprot*). Results also indicate that the coefficients have expected signs as hypothesized before except for use of hired labour and use of storage protectorant (Table 3).

Gender of households' heads (*gender*) is statistically significant at 1 percent level of significance and influence PHL positively. Results show that the probability of farmers experiencing post-harvest losses increases by 7 percent in male headed households as compared to female headed households. Results imply that the probability of PHL is higher among male farmers as compared to females. This is because females are very cautious with household food security and thus they store the crop with high care than males.

Table 6: Logit Regression Results on Determinants of PHL

Variable	dy/dx	Delta-method std. Error	Z	P>|z|
gender	0.066***	0.023	2.96	0.003
Age	0.084**	0.034	2.48	0.030
martalstatus	-0.033	0.022	-1.48	0.138
Lnworkdays	0.013**	0.006	2.32	0.020
hlabour	0.224***	0.011	1.99	0.046
Lnplotmarket	-0.005	0.006	-0.83	0.407
storageprot	0.027*	0.016	1.70	0.090
number of observations = 1565				

Significant level ******* ($p \leq 0.01$), ****** ($p \leq 0.05$) and ***** ($p \leq 0.10$)
Source: STATA output from NPS data (2008/2009, 2010/2011, 2012/2013).

Age of household head was found to be statistically significant at 5 percent to influence positively the maize post-harvest loss. The probability of household to experience maize post harvest loss increases by 8% by increase of one year in age of head of household. This is because the risk averse to adopt the modern technologies increases with increase of age which is supported by economic theory. The same results have been reported by other studies (Maremera, 2014; Tadesse, 2016).

On account to harvest working days (*lnworkdays*); is statistically significant at 5 percent and positively influence PHL. Results show that a day increase in harvest working days increases the probability of farmers experiencing PHL by 1 percent. Results imply that as working days increase chances of farmers experiencing post-harvest losses are greater. This is due to the reason that many harvest working days increases time the matured crop stays in farm of which the crops are hampered by various weather conditions. Dumpy conditions increase moisture contents leading to growth of micro-organisms and moreover lead to weight loss. Sunny conditions increase crop shattering hence high chances of losses. Results by Ayandiji and Adeniyi (2014), supports the findings and indicated that harvest work days had significant influence on PHL of plantain.

As regard to use of hired labour in harvesting (*hlabour*), it is positive and significantly affects PHL at 5 percent. Results show that the use of hired labour in harvesting increases probability of farmers experiencing post-harvest losses by 22 percent as compared to those who did not use hired labour. Results are contrary to the priori expectations and hypothesis that use of hired labour in harvesting was expected to have a negative influence on PHL.

Results imply that the more the farmers use hired labour in harvesting, the more the farmers experience PHL. This could be due to the reasons that, farmers that use hired labour in harvesting do not supervise them enough and that the hired labour do not abide to the post-harvest handling procedures. Moreover, most of the hired labours lack training and knowledge on post-harvest handling procedures; therefore, perform work only using their farming experience.

Taking into account use of storage protectants (*storageprot*); it is positive and significantly influence PHL at 1 percent. Results show that the probability of experiencing PHL increase by 3 percent to those farmers who used storage protectorants in their stored crops as compared to those who did not use storage protectorants. Results are in contrast to the priori expectations and hypothesis that the use of storage protectorants decreases the probability of farmers to experience PHL.

Results imply that as farmers use storage protectorants in their stored crops, the probability of experiencing loss increases. This could be due to the reasons the pests and insects that damage stored crops tend to be resistant to most of the common protectorants (insecticides and pesticides) with time. In addition most farmer do not use the recommended quantity of protectorants because either of high cost or lack of knowledge as it has been pointed out by other studies (Folayan, 2013; Adisa et al., 2015). The inefficiency of the protectorant have been also attributed to high relative humidity, sunlight and high temperatures and therefore creates better environment for micro-organisms, insects and pests to grow leading to high chances of losses.

5.4 Logit regression results on adoption of IPHSTS

The results of fixed effects logit regression model show that the probability of log-likelihood ratio is significant at 5 percent i.e. p=0.0294. This implies that the overall model is fit. Results show that only two (2) variables were found to be positive, and significantly influence PHL, these are; quantity of maize harvested and age of households' heads. In general the coefficients have expected signs as hypothesized before.

Results show that, quantity of maize harvested (*lnharvest*) is positive and significant at 1 percent in influencing PHL (Table 7). Results show that the probability of farmers adopting IPHSTs increase by 44 percent as quantity of maize harvested per area cultivated increase by one kilogram.

Table 7: Logit Regression Results on Factors influencing Adoption of IPHSTs

Variable	dy/dx	Delta-method std. Error	Z	P>|z|
Age	0.057**	0.027	2.15	0.031
Hsize	-0.068	0.097	-0.70	0.485
Lnfoodexp	0.036	0.137	0.26	0.793
Lnharvest	0.437***	0.158	2.76	0.006
fsize	-0.005	0.034	-0.16	0.875
extension	-0.310	0.346	-0.90	0.370
number of observations = 448				

Significant level ******* (p≤0.01), ****** (p≤0.05) and ***** (p≤0.10)
Source: STATA output from NPS data (2008/2009, 2010/2011, 2012/2013).

Results imply that the increase in the quantity of maize harvested increases the probability of adopting the IPHSTs by farmers. This is for the reasons that, the increase in quantity of maize harvested to most farmers, increases their surplus, of which has to be stored. Farmers have various purposes of storing maize, and for the crop to sustain while in storage, farmers adopt the storage facilities that match their expectations as such, more farmers adopt IPHSTs. Findings are supported by results of Omotilewa *et al*., (2016) which indicated that total harvest had positive significant influence on maize storage and maize storage length for consumption at harvest period.

As regard to age of households' heads (*age*); results show that it is positive and significantly influence adoption of IPHSTs loss at 5 percent. Results show that one year increase of age of households heads increase the probability of adopting IPHSTs by 6 percent. Results imply that as age increases, the probability of adopting IPHSTs increases. This could be due the reasons that farmers become more experienced in farming activities and become aware of the post-harvest handing procedures hence increases their probability of adopting the improved storage technologies.

6. Conclusion and policy implications

The overall objective of this study was to analyze factors influencing adoption of IPHSTs by smallholder maize farmers in Tanzania. Specifically, the study aimed at analyzing the determinants of PHL among smallholder maize farmers of the studied area, the study also aimed at determining the factors that influence adoption of IPHSTs in the studied area. Using a sample of 1620 households from the three waves of National Panel Survey (NPS), i.e., (2008/2009), (2010/2011) (2012/2013), descriptive analyses suggest that 9 percent of the smallholder farmers experience PHL in various stages of post-harvest chain and an average of 115 kilograms of maize per household were lost. Only 19 percent of the smallholder farmers had adopted IPHSTs. The results from Logit regression model showed that PHL was positively and significantly influenced by gender of households' heads, harvest working days, used of hired labour in harvesting and use of storage protectorant. Further, logit regression results on adoption of IPHSTs indicated that quantity of maize harvested and age of households' heads had positive significant influence on adoption of IPHSTs.

The current panel data study results do not differ much with the results from previous studies which employed cross-sectional and thus they are conclusive and not questionable. Therefore, the Government and development agencies or partners should emphasize and promote the adoption of IPHSTs by smallholder farmers in order to mitigate post-harvest loss. It would be pertinent if there is provision and support of extension education to farmers through trainings, seminars, and extension visits on proper post harvest management particularly crop handling and storage technologies is pertinent.

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